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Seasonal Allergies and Accidents*

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Abstract

Seasonal allergies affect over 400 million people globally, yet the broader economic consequences of pollen exposure remain understudied. Evidence from Japan's ambulance records suggests that high-pollen days are associated with increases in accidents, including traffic accidents and work-related injuries, which may reflect impaired cognitive performance. Retail scanner data and cellphone mobility records indicate that individuals already engage in avoidance behaviors, such as purchasing allergy products and limiting outdoor activities on weekends. This suggests that relying on individual self-protection may be insufficient to offset these risks, and thus greater government intervention may be warranted to mitigate pollen-related harm.

Keywords: Seasonal allergies, pollen, accidents, cognition, avoidance behaviors, climate change
JEL code: I12, J24, Q51, Q53, Q54

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1. Introduction

"Hay fever," also known medically as seasonal allergic rhinitis (SAR), is a common chronic disease triggered by exposure to airborne allergens, such as pollen and dust. These allergens cause various allergic symptoms, including a runny nose, nasal congestion, sneezing, and itchy eyes. It is estimated that up to 30% of the population in developed countries suffers from SAR, with approximately 400 million sufferers worldwide (Greiner et al. 2011). For instance, in 2021, 1 in 4 adults and 1 in 5 children in the U.S. experienced seasonal allergies (CDC 2023).[1]

The number of SAR sufferers is expected to rise as a warming climate accelerates pollen production, increasing pollen concentrations. From 1990 to 2018, pollen concentrations in the US increased by 21%, with the pollen season starting 20 days earlier than in 1990 and lasting 8 days longer (Anderegg et al. 2021). Figure 1 illustrates a strong positive correlation between pollen counts and maximum temperature (panel A) and the number of hot days above 30℃ (panel B) during the previous summer in Japan—our study area. This suggests that human-induced climate change may exacerbate the potential damage caused by pollen production.

Despite its widespread and increasing global prevalence, there is limited understanding of how pollen exposure affects outcomes beyond the obvious adverse health effects. Given the non-acute and less life-threatening physiological nature of SAR symptoms, people may have overlooked the potential negative consequences and costs of pollen exposure. Clinical studies have shown that pollen exposure can detrimentally affect cognitive performance—reducing attention span and increasing reaction time, suggesting that any daily activity requiring normal cognitive alertness and decision-making abilities may be affected. However, little is known about whether such cognitive stress translates into negative economic consequences, such as reduced labor productivity, in field settings.

To address this gap in the literature, we conduct the first investigation of the effects of acute and short-term pollen exposure on the incidence of accidents. These include traffic accidents and work-related injuries, which are arguably some of the most extreme consequences of cognitive impairment. Traffic accidents are the leading cause of accidental deaths globally, and hence, any factor influencing the risk of traffic accidents is of great relevance to social welfare.[2] Work-related injuries also warrant investigation, as they result in substantial productivity losses in the labor market. Furthermore, these accidents can cause negative externalities for individuals not

[1] Media coverage of seasonal allergies is on the rise. See, for example, Ramirez (2023) "Your pollen allergies are overwhelming? This might be why" in CNN, Agrawal (2024) "Spring allergy season is getting worse. Here's what to know" in the New York Times, and Jarvis (2024) "You're not imagining it. Your allergies are getting worse" in Bloomberg Opinion.

[2] Traffic accidents are the second leading cause of accidental death (after asphyxia), with an average of more than 4,000 deaths and 700,000 injuries per year for the period 2008 to 2019 (MHLW 2009; NPA 2022), in a total population of 127 million in Japan.

suffering from seasonal allergies but involved in the accidents.

Our analysis is facilitated by a comprehensive database we have compiled, which combines pollen counts, accidents, public awareness of pollen exposure, consumption, and mobility. Our primary data combines pollen counts with newly available administrative ambulance records, covering all ambulance calls related to accidents that occurred in Japan from 2008 to 2019. These accidents were particularly severe, requiring ambulance transport to hospitals. The dataset includes a wealth of information about each accident, including its location, date and time of the ambulance call, type and severity of injuries, and the age and gender of those involved. To examine whether individuals engage in avoidance behaviors, we use retail scanner data on allergy-related products and cellphone mobility records from 85 million users of Japan's largest mobile phone carrier.

Japan provides an ideal empirical setting for this study for several reasons. First, pollen monitoring stations are densely distributed nationwide—an uncommon feature in most countries. Second, pollen concentrations vary widely in space and time, allowing us to measure exposure with high precision and investigate potential nonlinear dose–response relationships. Third, pollen exposure in Japan is driven almost entirely by a particular species—Japanese cedar and hinoki cypress—enabling clean identification based primarily on pollen intensity.[3] This feature is important because individuals' sensitivity to an allergen, their reactions to related allergens, and their ability to develop tolerance all vary depending on the pollen source. By contrast, in numerous other regions, including North America and Europe, a small number of taxa dominate overall pollen counts (Lo et al. 2019), substantially limiting the usefulness of variation for identification. Finally, unlike prior studies restricted to a few schools or neighborhoods near monitoring sites, our analysis provides nationally representative estimates, alleviating concerns about external validity. We leverage daily levels of spatial and temporal variation in pollen counts of differing magnitudes to identify the effect of pollen on accidents.

There are five main findings. First, we present evidence that people are more likely to experience seasonal allergy symptoms on high pollen days than on low pollen days. This is based on data from internet search activity (Google Trends) and social media posts (Twitter data). We find that people tend to search and tweet about symptoms using keywords such as "runny nose," "nasal congestion," "sneezing," and "itchy eyes" as pollen levels increase. Similarly, we observe results for keywords related to sleep, such as "having a hard time falling asleep" and "feeling sleepy," indicating the negative impact of SAR on cognitive performance.

Second, we find that high daily pollen counts are associated with increased accidents. A

[3] The large-scale planting of Japanese cedar and hinoki cypress was initiated by the government to offset wartime and postwar overharvesting and accommodate the sharp increase in timber demand during the post–World War II high-growth period. Consequently, the species now comprise approximately 70% of the nation's 10.09 million hectares of planted forests (Forest Agency 2022).

100% increase in the daily pollen count leads to an increase in the number of daily accidents of 0.231 per million people. The relationship between pollen counts and the number of accidents is concave, suggesting that even low levels of pollen—which occur more frequently than higher levels—can have a significant negative impact on cognitive performance and thus on the incidence of accidents.

Third, we explore how the effects may vary by type of accident, severity of accident, and characteristics of the people involved. Interestingly, the effects are observed for all types of accidents, including traffic accidents, work-related injuries, sports injuries, and fire accidents. Using a unique measure of accident severity based on the initial clinical assessment by physicians at the time of hospital admission, we find that while the effects are more pronounced for less severe accidents, elevated pollen exposure also increases fatal accidents. Furthermore, consistent with the widespread prevalence of SAR, the effects are nearly universal across all age groups and both sexes.

These findings suggest that pollen exposure has a broad impact on "non-health" outcomes, such as cognition, productivity, and activities of daily living. For example, an increase in workplace injuries implies a detrimental effect on labor productivity and long-term earnings.[4] Therefore, current estimates of the costs of exposure to airborne allergens, primarily based on health outcomes, missed school days, and work absenteeism, may severely underestimate the true costs to society.

Fourth, we find that people are actively engaging in avoidance behaviors to reduce the risk of pollen exposure and alleviate allergy symptoms. Using retail scanner data, we show that people increase their spending on products that protect against seasonal allergies, such as medications, eye drops, and masks. Furthermore, using cellphone mobility records, we also show that some people even limit outdoor activities on weekends to reduce the risk of outdoor pollen exposure. To the extent that such behaviors are effective, we may be underestimating the true magnitude of pollen-induced accidents.

These results suggest that the status quo of relying on individual self-protection is insufficient to mitigate pollen-related harm. Considering the negative externalities of accidents and substantial social costs, additional government intervention appears warranted. One practical approach is a public information campaign, including a "pollen alert" system, that provides timely guidance tailored to forecasted pollen levels and offers standardized recommendations for the general public and firms. For the public, clear behavioral recommendations aligned with pollen forecasts—such as wearing masks, using air purifiers, relying on public transportation, or avoiding nonessential travel—could improve avoidance behavior. For firms, the guidelines could

[4] Broten et al. (2022) find that workers who are injured on the job face an average earnings penalty of 8%, which increases to 30% for those who are permanently disabled.

clarify when sick leave or remote work is appropriate for employees with severe seasonal allergies, recognizing that many are willing to avoid high-pollen environments but face work-related opportunity costs.

Finally, we combine our estimates of the impact of pollen on accidents with projections of future climate and the temperature-pollen count relationship shown in Figure 1 to illustrate the magnitude of the social costs of anthropogenic climate change. The "business-as-usual" scenario of the Intergovernmental Panel on Climate Change (IPCC)—predicting a 4.1℃ increase in summer temperature in Japan from 2076 to 2095—would result in an additional 1,823 pollen-induced accidents per year. By multiplying the resulting number of accidents by the average accident cost, we obtain an expected annual social cost of pollen-induced accidents of about $236 million. This estimated social cost is likely to be a lower bound because it does not include minor cases that do not require ambulance transport to a hospital.

While much of the existing literature on climate change has focused on the effects of rising temperatures on direct outcomes such as aggregate income, mobility, mortality, and agricultural outcomes (Carleton and Hsiang 2016; Dell et al. 2014), the increase in the number of seasonal allergy sufferers and the associated impairment in performance may be the indirect and undiscovered cost of anthropogenic climate change. Consequently, any action to mitigate the risk of a warming climate could have substantial societal benefits by preventing temperature-driven increases in airborne pollen.

It is important to note that the estimates presented here only begin to address the potentially significant social costs associated with rising pollen levels. If pollen exposure impairs cognitive function, it could significantly affect various daily human activities that require sustained cognitive attention. This research represents a first step toward understanding the full societal impact of pollen exposure, not just within a specific setting and country, but on a more global scale.

The remainder of the paper is organized as follows: Section 2 briefly describes the background, Section 3 describes the data, Section 4 presents the econometric model, Section 5 reports the main findings of this study, and Section 6 examines avoidance behavior. Section 7 reports the results of the projection of future climate change. Section 8 presents the discussion and conclusions.

2. Background

2.1. Pollen and seasonal allergies

SAR, a common chronic condition, arises when an individual's immune system reacts to airborne allergens like pollen and dust. This reaction prompts the immune system to generate antibodies, such as histamines and cytokines, to combat the perceived threat of pollen grains.

Consequently, the antibodies cause inflammation in the airways, leading to various allergic symptoms like a runny nose, nasal congestion, sneezing, and itchy eyes (Greiner et al. 2011).

SAR poses a global health concern as it can affect otherwise healthy individuals. Prevalence rates vary across countries, typically ranging between 10% and 30% in developed nations (Greiner et al. 2011; Schmidt 2016). However, this figure likely underestimates the true prevalence rate, as some individuals may not seek medical assistance for the condition. An increasing prevalence is driven by factors such as urbanization, adoption of Western lifestyles, and climate change (Schmidt 2016).

In Japan, the Japan Society of Immunology and Allergology in Otolaryngology has conducted a comprehensive epidemiological survey every ten years among otolaryngologists and their families since 1998. According to this survey, the prevalence rate of SAR has increased by approximately 10 percentage points each decade, rising from 19.6% in 1998 to 29.8% in 2008 and 42.5% in 2019, slightly exceeding the 10–30% prevalence reported in other developed countries. Although the prevalence rate peaks around middle age, a significant number of both young and older individuals also suffer from SAR (Matsubara et al. 2020).[5]

Because SAR is relatively mild and chronic, its economic costs are often underestimated. Apart from direct medical expenses such as medication and emergency room visits (Xing et al. 2023), as well as physician consultations and hospital admissions (Steinbach 2022), previous studies indicate that pollen allergies significantly contribute to absenteeism from work and school (Hellgren et al. 2010; Lamb et al. 2006).

Of particular relevance to this study, clinical research has demonstrated the adverse effects of SAR on cognitive performance. These effects often manifest indirectly through decreased sleep quality (Craig et al. 2004; Santos et al. 2006) and directly through the antibodies themselves affecting brain function (McAfoose and Baune 2009). For instance, Wilken et al. (2002) discovered that allergic adults randomly exposed to pollen exhibit poorer performance across various cognitive measures compared to non-exposed individuals. These measures include longer reaction times, reduced working memory, divided attention, and slower calculation. Unfortunately, medical studies have indicated that allergy medications such as antihistamines can also impair cognitive function due to side effects like drowsiness, dry mouth, and lethargy (Jáuregui et al. 2009; Kay 2000).

Previous studies examining the effects of seasonal allergies on non-health outcomes such as cognition in real-world settings have primarily focused on their impact on children's test performance (Bensnes 2016; Marcotte 2015, 2017). However, it remains unclear whether the negative effects of pollen on cognitive function extend to a substantially larger population of

[5] The prevalence rates of SAR in 2019 are 30.1% (age 5–9), 49.5% (10–19), 47.5% (20–29), 46.8% (30–39), 47.5% (40–49), 45.7% (50–59), 36.9% (60–69), and 20.5% (70–) (Matsubara et al. 2020).

prime-aged adults and, importantly, whether this potential cognitive stress could lead to adverse economic outcomes. This paper focuses on accidents, including traffic collisions and work-related injuries, as they represent the most severe forms of performance impairment. For instance, it is well-established that cognitive function is inversely correlated with the likelihood of motor vehicle accidents (Anstey et al. 2005, 2012).[6] Vuurman et al. (2014) contend that the impairing effects of allergic rhinitis on driving are comparable to those of a blood alcohol content of 0.05%, the legal limit in many countries. Similarly, most workplace injuries result from distraction (European Commission 2009). Nonetheless, we acknowledge that cognition is not the sole underlying mechanism, as pollen exposure is also clinically associated with mood, fatigue, and emotion (Dowlati et al. 2008; Kronfol and Remick 2000).

2.2. Warming climate and pollen

Higher temperatures and carbon dioxide (CO_2) concentrations have been found to increase pollen production, implying that climate change is expected to significantly affect pollen concentrations and the duration of pollen seasons. Anderegg et al. (2021) tracked pollen trends at 60 pollen stations in the United States from 1990 to 2018. They found increases of 20.9% and 21.5% in annual and spring (February–May) pollen concentrations, respectively. The pollen season started 20 days earlier and lasted eight days longer. Further, they conducted a model selection analysis to identify the main drivers of pollen proliferation. They found that the mean annual temperature is the strongest predictor of the above pollen metrics among eight climate variables, which include temperature, precipitation, frost days, and CO_2 concentrations. Increased pollen abundance, earlier onset of the pollen season, and longer duration of the pollen season have also been observed in Europe (D'Amato et al. 2007; Ziello et al. 2012; Hamaoui-Laguel et al. 2015).

This pattern also appears in our Japan data. Using station-year observations from 120 pollen monitoring stations (2008—2019), we find that higher maximum temperatures and more days above 30℃ in July and August of the *previous* summer correlate with higher average daily pollen counts from February to May (Appendix Figure A1).[7]

Figure 1, mentioned in the introduction, shows the relationships between pollen counts and temperatures in the previous summer using the same data. The binscatter plot exploits the variation in pollen counts within the same pollen monitoring station over time by controlling for station fixed effects (FEs). The linear slope of 167.4 (t-stats= 11.2) in panel A indicates that a

[6] Smith (2016) shows that one hour of sleep loss increases the likelihood of being involved in a fatal drowsy driving crash by 46%.

[7] For instance, the relatively cool summer of 2009 was followed by low pollen counts in spring 2010, whereas the hot summer of 2010 preceded high counts in spring 2011.

1℃ increase in maximum temperature in the previous summer is associated with an additional 167 grains/m^3 of daily pollen on average in the following spring. As the mean and median daily pollen counts of 120 stations in the same period are 955 and 712 grains/m^3, respectively, such an increase can be sizable. Similarly, the slope in panel B is 23.7 (t-stats= 11.2), indicating that ten more hot days above 30℃ in the previous summer could increase the daily pollen count by 237 grains/m^3 in the following spring.

In summary, the evidence to date suggests that human-induced climate change has increased the intensity of pollen seasons in different parts of the world. Expected temperature increases due to global warming are likely to amplify and accelerate this trend in the coming decades (Ziska et al. 2019). For example, Zhang and Steiner (2022) project that climate change will *further* accelerate the arrival of the pollen season (by up to 40 days), increase the duration of the pollen season (by about 19 days), and consequently increase the total annual pollen load (from 24% to 40%) in the United States.

3. Data

We have assembled a comprehensive dataset to examine the impact of pollen exposure on accident rates. In our primary analysis, we merge daily airborne pollen counts with newly available ambulance records documenting accidents that occurred between 2008 and 2019 in Japan. To our knowledge, this is the first study to use this dataset in economic research. For greater clarity, supplementary data used to examine symptoms (Google Trends and Twitter data, detailed in Section 5.1) and avoidance behaviors (retail scanner data and cellphone mobility records, discussed in Sections 6.2 and 6.3) will be described later. For more information on the data sources, see Appendix H.

3.1. Airborne pollen

We obtain airborne pollen data from the Japanese Ministry of Environment's pollen monitoring system, known as "Hanako-san." This system provides hourly measurements of pollen counts (grains/m^3) for Japanese cedar and hinoki cypress. Pollen season calendars for major plant species (Appendix Figure A2) indicate that most pollen is released between February and May, when these two species constitute the dominant sources. Comprehensive pollen count data have been available since 2008, published on the Ministry of the Environment's website. Moreover, during the pollen season, weather forecasts in Japan routinely include information on pollen levels alongside temperature and precipitation. Television broadcasts typically report both current-day and weekly pollen forecasts; an example is provided in Appendix Figure A3. Thus, the cost of accessing such information is nearly negligible.

Throughout Japan, there are a total of 120 pollen monitoring stations. Panel A of Figure 2 displays the locations of all monitoring stations as of 2019.[8] On average, each of the 46 prefectures has two to three monitoring stations, primarily situated in urban areas with high population densities (Wakamiya et al. 2019).[9] The number of pollen monitoring stations is remarkably high considering the country's size. For instance, the United States, which is 26 times larger than Japan, only has 74 pollen monitoring stations nationwide.

Panel B of Figure 2 plots the cumulative distribution of the distance from the nearest pollen station to the centroid of each emergency response unit, our regional unit of analysis, as described in Section 3.2. The mean and median distances from pollen stations are 25.4 and 17.5 kilometers, respectively. Even with a conservative threshold of 48 kilometers (30 miles) for pollen measurements to be valid (Chalfin et al. 2019), 90.2% of all units fall within this threshold.[10]

The high density of stations across the country enables us to: (i) accurately measure pollen exposure, (ii) provide nationally representative estimates of pollen exposure (unlike previous studies limited to a few schools or districts near pollen stations), and (iii) include the continuous variable of pollen exposure at various levels as a regressor to examine potential nonlinearity in the dose-response (unlike previous studies that only included a dichotomous variable defining high pollen days).

Pollen counts are monitored from February to May each year to cover the blooming season of Japanese cedar and cypress (as shown in Appendix Figure A2). The exception is Hokkaido Prefecture in the far north, where monitoring occurs at four stations and the observation period is delayed by one month, from March to June. We aggregate the monitor readings to obtain the daily level by summing the hourly observations to calculate the accumulated number of pollen grains counted within 24 hours. Additionally, weather covariates from nearby weather stations are included in the same dataset. Specifically, hourly temperature, precipitation, and wind speed are recorded. Likewise, we aggregate these variables to obtain daily levels.

As pollen in Japan typically disperses over 100 kilometers and remains airborne for more than 12 hours, nearly all regions, including sparsely forested cities, can be contaminated by airborne pollen (Yamada et al. 2014). Figure 3 illustrates the average pollen counts by municipality for the period 2008 to 2019. The figure demonstrates that while the entire country is

[8] The number of pollen stations has remained at 120 since 2008, so our estimates are not affected by changes in the number of stations. The movement of stations is limited to a handful of stations, and the distance of movement is minimal.
[9] Okinawa prefecture, the southernmost remote island in Japan with a different climate than the rest of the country, has no pollen station because little pollen is observed. We exclude Okinawa from the entire analysis.
[10] Chalfin et al. (2019) examine the effect of pollen on crime in US cities using criminal records from stations within 30 miles (48 kilometers) of the city center, while the National Allergy Bureau suggests that pollen measurements are valid within a 20-mile (32 kilometers) radius of each station.

exposed to pollen, there is considerable spatial variation across the nation, even within narrowly defined areas. The source of the identifying variation is discussed in detail in Section 4.2.

3.2. Ambulance records

Our comprehensive administrative data on accidents and injuries are sourced from the Fire and Disaster Management Agency (FDMA) of the Ministry of Internal Affairs and Communications, Japan. This dataset encompasses all ambulance calls, except those from the Tokyo metropolitan,[11] from 2008 to 2019 that required ambulance transport. Registration of all ambulance records in the FDMA's online system became mandatory in 2008. Because ambulance service in Japan is free for the public, there is no differential sample selection based on socioeconomic status, unlike in countries such as the United States, where ambulance use varies by health insurance status (Meisel et al. 2011).

In total, 14.7 million accidents were recorded between 2008 and 2019, averaging 1.2 million accidents annually.[12] The dataset provides detailed information for each accident, including the accident's location, the date and time of the ambulance call, the accident type, the severity of injuries, and the age and gender of the individuals involved.

Two features of this dataset are particularly valuable for our study. First, it records the type of accident involved, including traffic accidents, work-related injuries, sports injuries, and fire accidents. Second, it provides information on the severity of the injuries sustained. This measure is highly reliable because it is based on the initial clinical assessment conducted by physicians upon the patient's admission to the hospital. Injury severity is classified as fatal or near-fatal, severe, moderate, or minor, where "severe" cases require more than three weeks of hospitalization and treatment, "moderate" cases require less than three weeks, and "minor" cases do not require hospitalization.

Ambulance records offer two key advantages over vital statistics: they capture non-fatal but severe injuries that vital statistics may miss, and they record accidents on the exact day they occur, avoiding the measurement error associated with the reporting delays sometimes present in vital statistics.

The geographical unit in ambulance records is an emergency response unit (referred to as "unit"), which constitutes the primary level of ambulance service in Japan. While many units

[11] Tokyo is excluded from the sample because (i) metropolitan Tokyo (23 wards of central Tokyo and most cities in Tokyo) falls under a single ambulance operating system (the Tokyo Fire Department), which is likely to introduce substantial measurement error in assigning pollen counts, and (ii) data from metropolitan Tokyo are only publicly available from 2016 onwards. Nevertheless, we later include data from Tokyo for the period 2016–2019 to verify that our results are robust to its inclusion in Table 3.

[12] Ambulance records also include medical emergencies (72.3% of all records). As our focus is on accidents, we extract data on five types of accidents from the ambulance archives: traffic accidents, work-related injuries, sports injuries, fire accidents, and other accidents, which account for 25.9% of all records. The remaining records are self-injury, assault, drowning, natural disasters, and other categories (1.8%).

represent municipalities themselves, some small municipalities combine to form a unit, enhancing the efficiency of ambulance service. As of 2019, 1,700 municipalities (equivalent to counties in the United States) across 46 prefectures (equivalent to states in the United States) form 705 units. We aggregate accident records to the unit-day level by adding hourly observations within the units.[13]

3.3. Sample construction and summary statistics

To form our primary sample, we merge ambulance records by unit-day with corresponding pollen counts from nearby monitoring stations, recorded on the same day. Consequently, the primary sample encompasses records from February to May, the peak pollen seasons, for all prefectures except Hokkaido, in which records span from March to June, covering 2008 to 2019.

Table 1 presents summary statistics for our primary estimation sample, comprising 970,309 unit-day observations. On average, there are 33 daily accidents per million people. Traffic accidents emerge as the most prevalent type, constituting 37.6% of all incidents, followed by work-related injuries (3.5%), sports injuries (2.6%), and fire accidents (0.5%). Other accidents, not categorized within these categories, account for more than half of all incidents (55.8%).[14] The average daily concentration of airborne pollen is 984 grains/m^3, with a standard deviation of 2,135.[15]

4. Econometric model

4.1. Estimating equation

We estimate the effect of short-term pollen exposure on accident rates, net of any potentially confounding factors:

$$Y_{it} = \beta log\ (Pollen_{it}) + \gamma X_{it}^{'} + \alpha_i + \alpha_{time} + \varepsilon_t, [1]$$

where the dependent variable Y_{it} represents the number of accidents per million people in unit i on date t. Taking the logarithm of pollen counts aligns with the nonlinearity observed in clinical studies (Erbas et al. 2007) and addresses the right skewness of pollen count distributions.[16] Later,

[13] The timestamp of each accident reflects the time it was reported to emergency response units, not the actual time it occurred. This may introduce some measurement error with respect to the hour (more likely) than the date. Consequently, we aggregate accidents at the daily level, following the approach used in literature (e.g., Park et al. 2021).

[14] These accidents range from minor to major and include: (i) slipping and falling on a step, (ii) slipping and falling on a snowy road, (iii) spilling a pot and getting burned, and (iv) slamming a finger in a screen door.

[15] We truncated the pollen counts at the 99.9th percentile (55,104 grains/m^3) to account for outliers.

[16] Appendix Figure A4 presents a histogram of daily pollen counts and their logged values for the period 2008–2019. We add one to account for zero pollen counts (0.83%) before taking the log. In Table 3, we show that our results are robust to dropping these observations and taking the log without adding one. Bensnes (2016) and Marcotte (2017) also take the log form of pollen counts.

we present results from alternative specifications, such as level-level or "dose-response," and estimate the Poisson model to explicitly accommodate the non-negative discrete nature of accident counts and to gauge the sensitivity of our findings to zero observations. The parameter of interest, β, quantifies the change in the outcome associated with a 100% increase in pollen counts. The unit FE (α_i) controls for geographic disparities in health and pollen concentrations.

The high granularity of our data enables us to incorporate multiple sets of high-dimensional time FEs (α_{time}). The baseline specification includes prefecture-by-month (α_{pm}), month-by-year (α_{my}), and day-of-week FEs (Deryugina et al. 2019). Prefecture-by-month FE controls for any seasonal correlation between pollen counts and accidents, allowing this correlation to vary across prefectures. Month-by-year FE flexibly controls for nationwide time-varying shocks during our sample period. Finally, day-of-week FEs account for within-week variation in accidents. This approach enables us to compare days within the same month and unit that differ in pollen concentration across years, thereby mitigating concerns that other seasonal trends in accidents might bias the results.

The X_{it}' flexibly controls for daily variations in weather covariates. We include seven indicators for 5°C intervals of daily average temperatures, ranging from 0°C or less to 25°C or more. For daily precipitation, we include four indicators (no rain, less than 1 mm of rain, 1 mm to 2 mm of rain, and more than 2 mm of rain). We also control for the average wind speed and duration of darkness, the time between dusk and dawn, which is an important factor for traffic accidents (Bünnings and Schiele 2021). Finally, we control for the logged population, which is related to population density and congestion (once with the unit FE included), potentially affecting the risk of accidents (Abouk and Adams 2013).

We cluster all standard errors at the pollen monitoring station (N= 120)—the level of underlying variation in our treatment variable (Abadie et al. 2023)—to account for possible serial correlation and weight all estimates by the relevant population in cases where the dependent variable is expressed in per capita terms.

4.2. Identifying variation

We leverage daily variations in pollen counts to identify the impact of pollen on accidents. The underlying assumption for β in equation [1] to reflect the causal impact of pollen is that the temporal, seasonal, and geographic variations in daily pollen counts, *net* of confounding factors, would be considered exogenous. While it is not feasible to directly test this assumption, it is broadly plausible, as discussed below. First, we demonstrate that there remains substantial residual variation in pollen concentrations even after controlling for location and time FEs, along with comprehensive sets of weather controls. Subsequently, we discuss the arguably "exogenous" determinants of such daily pollen count variations.

We start with documenting significant spatial and temporal variation in pollen counts even within relatively narrow regions and periods (i.e., after controlling for prefecture-by-month and month-by-year FEs). As an example, Figure 4 displays the daily pollen counts from 2017 to 2019 at three monitoring stations in Ibaraki Prefecture, located northeast of Tokyo (part of the Kanto region, as depicted in Appendix Figure A2). Temporal variations in pollen exposure occur within each station, along with spatial variations across the three stations within the short time window. Furthermore, this pattern is not systematic; while Station C recorded the highest pollen counts in most months in 2017 and 2018, Station A recorded the highest pollen counts in 2019.[17] This observation illustrates that areas experiencing high pollen exposure in certain years encounter low pollen exposure in others, suggesting substantial idiosyncratic variation in pollen across areas over time.

Obviously, such patterns could be partially explained by contemporaneous local weather conditions. Therefore, adequate control for weather covariates, as in equation [1], is important to mitigate concerns that "naturally occurring" processes of pollen production may contribute to accidents independent of pollen counts. For example, car accidents increase on rainy days, and rain is clearly negatively correlated with pollen counts, potentially introducing downward bias in our estimates. However, pollen counts are only weakly correlated with local weather covariates; a regression of the logged pollen counts on granular weather controls included in the main specification (temperature, precipitation, wind speed, and darkness) yields an R-squared value of only 14.5%,[18] and adding the aforementioned location and time FEs raises it to at most 40.1%.

Why do these "intuitive" weather covariates have limited explanatory power for daily pollen variations? According to the Ministry of Environment in Japan (MOE 2022), cedar pollen becomes more abundant about 7 to 10 days after it begins to shed. About four weeks after that is the *peak* pollen period, and within this period, pollen levels are particularly high when the weather is warm, dry, and windy, while pollen levels are low when the weather is rainy and/or cool. To visualize these relationships, Figure 5 extracts data from Station A in 2019 from Figure 5, adds the average temperature, and indicates days with any precipitation. The figure shows that pollen concentrations are high on warm days and low on rainy days during the peak season, while this relationship is much weaker during the off-peak season, partly explaining the low R-squared value.

[17] This observation is not specific to this particular prefecture. The same pattern of reversal can be observed in another example from Niigata Prefecture, as depicted in Appendix Figure A5.

[18] This low R-squared does not result from how precipitation and temperature are coded. For example, changing both to dummies for deciles of precipitation and temperature changes it to 16.8%, and further interacting these temperature and precipitation dummies increases it only to 17.4%. Moreover, it is not attributable to long distances between weather stations and pollen monitoring stations, as presented in Table 3.

The natural question that follows is what factors determine the peak of the pollen season. Pollen studies have historically been popular in Japan, and there is accumulated scientific evidence to guide us in answering this question. It is widely documented that the peak of the pollen season is influenced by the preceding winter temperature (e.g., Kishikawa 1988). This makes biological sense because summer temperature determines the growth of pollen-bearing trees and, thus, pollen quantity, as shown in Figure 1, while winter temperature determines the timing of pollen onset and peak shedding.[19]

Indeed, we find a clear negative relationship between winter temperatures and the timing of the pollen season peak. Specifically, warmer January temperatures are associated with fewer days from the start of the year until the first day when pollen counts exceed 5,000 grains/m³ (approximately the 96th percentile), after controlling for monitoring station FEs (Appendix Figure A6). This pattern indicates that warm winters trigger earlier pollination and accelerate the seasonal peak.

Therefore, the *interaction* of the peak determinant and daily weather fluctuations, even conditional on very granular daily weather controls, can be a source of plausibly exogenous variation in daily pollen counts that is not correlated with other time-varying local determinants of accident risk. Another exogenous source of pollen variation is daily wind patterns (Iwaya et al. 1995). Because pollen can travel long distances (Yamada et al. 2014), wind direction on a given day provides us with *nonlocal* pollen variation that can be used to identify the effect of pollen exposure independent of local weather conditions.[20]

In summary, factors determined long before the start of the pollen season (i.e., winter temperature) that interact with contemporaneous weather conditions, as well as a component of contemporaneous local weather conditions that drives the idiosyncratic movement of pollen (i.e., wind direction), are some (but of course not all) of the sources of exogenous variation that we exploit to credibly identify a causal effect of pollen on accidents. We also illustrate the robustness of our results by estimating alternative specifications that include more or less stringent FEs to ensure that our results cannot be explained by specific unobserved seasonal or regional patterns, as well as stricter controls for weather conditions.

[19] Already in 1988, Kishikawa (1988) wrote: "The sum of these pollen counts correlated with the mean temperature in July of the previous year ($r = 0.878$, $p<0.001$) and the beginning of the pollination season correlated with the mean temperature in January ($r = -0.765$, $p<0.001$)."

[20] To minimize measurement error due to *local* pollution transport (e.g., from traffic or local power plants), Deryugina et al. (2019) restrict the influence of wind directions (their instrumental variable) on pollution to be the same for all monitors within the same geographic regions, mainly to exploit variations in *nonlocal* pollution from other regions. We do not adopt this approach because 1) the variation in pollen concentrations is mainly due to nonlocal transport (i.e., pollen-emitting trees in the mountains), while the monitors are mostly located in urban areas with high population densities, 2) technically, with only 120 pollen monitors across the country, the geographic regions containing multiple monitors become too large to adequately capture even nonlocal transport, and 3) more fundamentally, the wind directions affect the levels of pollen and pollution simultaneously.

To directly visualize the identifying variation underlying the baseline specification, we display the distribution of residuals from a regression of logged daily pollen counts on all the controls in equation (1), namely unit, month-by-year, month-by-prefecture, and day-of-week FEs, as well as weather covariates (precipitation, temperature, wind speed), darkness, and logged population. We summarize this residual variation using the interquartile and interdecile ranges across prefectures and years (Cabral and Dillender 2024). Both measures indicate substantial within-prefecture and within-year variation, confirming that our estimates are not driven by any single prefecture or any particular year (Appendix Figure A7).

5. Main results

5.1. Symptoms of seasonal allergies

Before presenting our main findings, we first examine whether individuals are more prone to experiencing seasonal allergy symptoms on high pollen days than on low pollen days. This analysis is based on data sourced from both Internet search activity (Google Trends) and social media posts (Twitter data).

We use publicly available Google Trends data focusing on two broad categories: (1) pollen-related keywords and (2) symptom-related keywords spanning from 2016 to 2019 at the prefecture-day level (N= 21,551). The Google search index reflects the popularity of search terms, ranging from 0 to 100 within a given prefecture and on a specific day, relative to the total searches within the specified period.[21]

Figure 6 illustrates the outcomes for symptom-related keywords such as "runny nose," "nasal congestion," "sneezing," and "itchy eyes" (see Appendix Table B1 for the comprehensive list of search terms employed). Panel A shows the time series of the Google search index for these keywords alongside the daily pollen counts (grains/m^3), using data from 2018 as an example. These variables exhibit close alignment over time. Panel B confirms this positive relationship in the binscatter plots, which show the relationship between logged daily pollen counts and the search index after adjusting for prefecture-by-month, month-by-year, and day-of-week fixed effects, as well as weather covariates, darkness, and logged population. A 100% increase in daily pollen counts leads to a 3.6-point rise in the search index on a scale of 0–100, with a mean of 30.4 (p-value<0.01). Similar patterns are observed for pollen-related keywords, such as "pollen," "pollen allergy," and "Japanese cedar pollen," as displayed in Appendix Figure B1.

We replicated the relationship between pollen counts and keywords using public Twitter

[21] The 2016 cutoff is motivated by data completeness and the fact that Google changed its data collection system on January 1, 2016. We follow Brodeur et al. (2021) to construct Google Trends data at the daily level over multiple years, using overlapping periods of daily and weekly data.

data spanning from 2016 to 2019 at the prefecture day level.[22] The sole distinction from the previous analysis is that the dependent variable now represents the number of tweets containing the same two keyword sets. Individuals tend to tweet these keywords more frequently on days with high pollen levels (Appendix Figure B2).

An advantage of Twitter data compared to Google Trends data is that, while the sample is biased towards younger cohorts, individuals often express emotional states in tweets (Baylis 2020; Burk et al. 2022). Therefore, we collected data on sleep-related tweets (Heyes and Mingying 2019), specifically those mentioning "having a hard time falling asleep" and "feeling sleepy," to gauge decreased sleep quality and daytime sleepiness. Individuals seem to encounter more sleep-related issues as pollen levels rise (Appendix Figure B3). This "first-stage" evidence suggests that individuals are experiencing typical seasonal allergy symptoms, and some are evidently aware of their exposure.

5.2. Basic results

Figure 7 displays binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3) and the number of accidents per million people. It encompasses all accidents (panel A), followed by specific accident types by frequency, excluding "other" accidents: traffic accidents (panel B), work-related injuries (panel C), and other accidents (panel D). These plots account for unit, prefecture-by-month, month-by-year, and day-of-week FEs, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Each figure presents a generally linear relationship with logged pollen counts, with a slight flattening at very high pollen concentrations. This simple plot demonstrates a robust connection between pollen concentration and accident occurrences, a relationship we formally examine below.

Table 2 presents the key estimates from equation [1]. Column (1) shows that a 100% increase in daily pollen count is associated with a 0.231 increase in daily accidents per million people. This result is precise and highly statistically significant (p-value<0.001, t-stats= 14.0). Relative to the average daily accident rate of 33.03, this represents a 0.7% increase, implying an elasticity of 0.0070 (= 0.231/33.03). To contextualize our findings, Sager (2019) reports that the elasticity of road traffic accidents with respect to $PM_{2.5}$ in the UK is about 0.06. While a direct comparison requires considerable caution, as Sager (2019) includes all traffic crashes with any personal injury (not always associated with ambulance transport), our elasticity is approximately one-tenth of that figure.[23] As shown in the heterogeneity analysis in Section 5.4, our elasticity is even higher for severe accidents (e.g., 0.033).

[22] We assign a prefecture based on the location at the time of the tweet.
[23] If we focus only on traffic accidents, column (2) of Table 2 shows that the elasticity is 0.0063 (0.079/12.41), which is very similar to the overall elasticity.

Columns (2)–(5) of Table 2 demonstrate that, although the magnitude varies by accident type, elevated pollen concentration is associated with increased occurrences across all types. For instance, the rise in the incidence of work-related injuries, albeit constituting a small share (3.5%), underscores the substantial health risk pollen exposure poses to workers and its potential adverse impact on labor productivity. We discuss the monetary values of pollen-induced accidents in Section 7, where we project potential damages from climate change.

Importantly, our estimates provide a lower bound on pollen's impact on accidents because the ambulance records analyzed exclude minor accidents that do not require ambulance transport. Furthermore, injury severity is evaluated upon hospital admission, potentially leading to an underestimation of eventual fatalities.[24]

Dose-response—. We also examine dose responses more flexibly by estimating a nonparametric binned regression in which the logged daily pollen counts in equation [1] are replaced with indicator variables for each decile of the daily pollen *levels*. The estimates reveal a clear concave relationship, indicating that even relatively low pollen levels—substantially more common than extreme levels—can meaningfully affect the incidence of accidents (Appendix Figure C1). Importantly, this concave dose–response pattern also highlights the potential benefits of reducing pollen concentrations, even in countries/settings where overall pollen levels are lower than those observed in our study. Furthermore, the shape of the function explains why the level-log specification in equation [1] fits the data well.

5.3. Robustness

Our findings regarding the impact of pollen on accidents remain robust to a battery of specification checks. These checks include variations in location and time FEs, different ways of constructing regressors and outcomes, alternative specifications, and placebo exercises.

Robustness—. Table 3 presents the results of robustness checks and extensions. Our findings remain robust across various ways of constructing pollen concentration measures including an inverse distance-weighted average of three nearby stations (columns 2 and 3), incorporating pollution covariates (SO_2, NO_2, CO, OX, PM_{10}) as potential confounders (column 4),[25] and introducing the full interaction of temperature and rain dummies to further control for

[24] For example, the number of work-related injuries, including injuries of all severity levels, captured by our ambulance records in 2019 is 50,578, while the total number of work-related injuries resulting in either death or at least four days of absence from work reported to the Ministry of Health, Labour and Welfare (MHLW) is 125,611 (MHLW 2020). Similarly, the number of traffic accidents captured by our ambulance records in 2019 is 368,680, while the total number of traffic accidents resulting in death or injury reported to the National Police Agency (NPA) in the same year is 464,990 (NPA 2022). Thus, approximately 40% and 80% of all work-related injuries and traffic accidents, respectively, are captured by our ambulance records.

[25] Pollen seems to exert an independent effect from pollution, as the correlation between pollen counts and other pollutants is extremely low (0.02–0.12). This is likely because pollen grains are relatively large (≈30 μm) compared

weather influence (column 5). Columns (6) and (7) address potential measurement errors in pollen counts—our key regressor—and in weather variables, which serve as key controls. Our results remain robust when the sample is restricted to units located within 48 kilometers of pollen monitoring stations, minimizing measurement error due to spatial misalignment between measurement points and exposure locations (column 6). Likewise, restricting the sample to observations linked to pollen stations located within 8 kilometers (0.5 miles) of weather stations (column 7) addresses concerns that weak correlations between weather and pollen may arise from greater station distance.[26] Our results remain robust when including data from Tokyo for the years 2016–2019 (column 8). The unweighted OLS estimates are larger than those from the weighted OLS specification (weighted by population in each emergency response unit), suggesting that the effects are stronger in less populated and rural regions (column 9).

To address the possibility that the effect of pollen may appear with a lag or temporal displacement, we estimate the following distributed lag model:

$$Y_{it} = \sum_{k \in K} \beta_k \, log\ (Pollen_{i,t-k}) + \gamma X'_{it-k} + \alpha_i + \alpha_{time} + \varepsilon_t, \quad [2]$$

where we include logged pollen counts and weather covariates (precipitation, temperature, wind speed) for the observation date and adjacent days within the time horizon K to mitigate concerns about autocorrelation. Our parameter of interest is the sum of coefficients (= $\sum_{k \in K} \beta_k$) from equation [2] with varying windows from $K = 0$ to 14.[27]

We find that the same-day effect ($K = 0$) effectively captures the bulk of the overall impact, with cumulative effects remaining relatively stable when the window is extended up to two weeks (Appendix Figure C3). This pattern is unsurprising and consistent with the short-lived nature of pollen-induced symptoms: although allergic reactions can occur within minutes of exposure, their effects typically last no longer than four to eight hours (Skoner 2001). Another approach to capturing dynamic effects is to temporally aggregate data at coarser intervals (Burke et al. 2018). Column (10) of Table 3 reports estimates using data aggregated to the weekly level to capture pollen effects that may persist over the week, such as those arising from deteriorated sleep quality. It is reassuring that this estimate closely aligns with the baseline estimate in column (1).

with pollutants such as PM_{10}, which are approximately 10 μm. Further, we examine the interaction of pollen with the arguably most harmful pollutant (PM_{10}). We find minimal evidence substantiating that pollen's effect is amplified on days with higher air pollution, likely because pollution levels in Japan are relatively low (Appendix Table C1 and Figure C2). Note that $PM_{2.5}$ data are available only from 2014 onward, and the results are robust to replacing PM_{10} with $PM_{2.5}$ (not shown), as the two measures are highly correlated (correlation = 0.84).

[26] Owing to the dense network of weather stations across the country (over 840 weather stations compared with 120 pollen monitoring stations), the distance between the two types of stations is generally short: Over 78% are located within 8 kilometers (0.5 miles) of each other.

[27] This approach is econometrically similar to a widely used alternative specification in the literature that estimates equation [1] with an extension of the outcome window to subsequent days (e.g., Deryugina et al. 2019).

We find that our estimates are robust to alternative specifications with more or less stringent FEs, including date FEs, ensuring that our results are not driven by specific unobserved seasonal or regional patterns (Appendix Figure C4). Additionally, our conclusions remain unchanged under different clustering choices, including two-way clustering by monitoring stations and dates to additionally account for potential spatial correlation, clustering at the broader prefecture level (46 prefectures) rather than only at pollen monitoring stations (120 stations), and the use of spatially clustered standard errors following Conley (1999) (Appendix Table C2). The results likewise remain stable under alternative functional-form assumptions: Both a log–log specification and a Poisson pseudo-maximum likelihood (PPML) model, which accommodates the count nature of accident outcomes, yield estimates consistent with the baseline (Appendix Table C3).[28]

Placebo—. We conduct two placebo exercises to assess whether unobserved seasonal or regional patterns drive our results. First, when pollen counts are falsely assigned to the same calendar day in the previous or subsequent year, the resulting estimates become substantially smaller and statistically insignificant (Appendix Table C4). Second, when we relate logged daily pollen counts to the daily number of emergency ambulance transports for cancer cases—a condition unrelated to short-term pollen exposure—we find no discernible pattern (Appendix Figure C5).[29] Collectively, these exercises reinforce that our main findings are not driven by specific unobserved seasonal or regional trends.

Replication—. Traffic accidents are recorded separately in police records, encompassing those causing personal injury, and reported to the National Police Agency from 2019 to 2020 (see Appendix D for data specifics). We compare mortality estimates from traffic accidents using ambulance records—our main data source—with estimates based on police records and find that the two are similar in magnitude (Appendix Table D1). Although the estimate using police data appears slightly larger, they are not statistically distinguishable from each other.[30] This underscores the robustness of the pollen effect across various samples gathered by distinct government agencies with differing crash definitions, thereby strengthening the internal validity of our findings. Furthermore, this suggests that selection into the ambulance records—arising from factors such as distance to hospitals, or individuals' preferences—may not be substantial.

5.4. Heterogeneity

Severity—. Figure 8 illustrates the estimates along with a 95% confidence interval for each

[28] PPML estimate converted to the level is similar to the baseline estimate, reassuring us that our results are not sensitive to zeros in the outcome.
[29] Ambulance records include detailed diagnostic information (equivalent to ICD10) starting in 2015.
[30] One possible reason for this observation is that police records include all deaths from traffic accidents within 24 hours, unlike ambulance records, which only include deaths occurring at hospital admission.

severity level. The estimates diminish as the severity level rises, yet remain positive and statistically significant across all levels, including death/fatality. The estimates for more severe accidents exhibit a larger magnitude *relative* to the lower baseline compared to those for less severe accidents, indicating higher elasticities for more severe accidents. Specifically, the elasticity for death/fatality (0.013) is roughly double that of minor accidents (0.006).

Other heterogeneity—. The ambulance records contain additional details regarding the accidents and the individuals involved. Figure 9, using all accident samples, investigates the heterogeneous treatment effects apart from severity. Panels A and B explore demographic heterogeneity, focusing on age and gender. Across all age groups and genders, statistically significant effects are observed, with magnitudes relatively similar to the means shown on the far right of the figure. The only deviation is a slightly larger effect observed in the elderly (>65), even when compared to the high baseline mean. This observation aligns with the heightened vulnerability of the elderly to environmental externalities, such as the relationship between heat, cold, pollution, and mortality (Carleton and Hsiang 2016; Cohen and Dechezleprêtre 2022; Jia and Ku 2019; Barwick et al. 2024).

Panel C of Figure 9 investigates heterogeneity by accident location. Accidents at home are also increasing, indicating the challenge of completely avoiding outdoor pollen, which can cling to clothing (e.g., wool coats) and easily enter indoor spaces. This may also reflect the prolonged impact of outdoor pollen exposure. Panel D illustrates that pollen's effect is more pronounced on weekends compared to weekdays. While individuals have greater flexibility to stay home and evade exposure on weekends by postponing non-essential trips, those going out might be less experienced drivers who typically refrain from weekday commutes or individuals taking recreational trips to unfamiliar destinations, rendering them potentially more susceptible to heightened pollen exposure risks. Our findings suggest that the latter scenario outweighs the former in this context.

Over time—. Finally, we divide the 12-year sample period (2008–2019) into four three-year intervals. Panel E of Figure 9 reveals a slight decrease in sensitivity to pollen-related accidents in the later periods compared with the earlier ones, likely reflecting advances in medication, as newer seasonal allergy drugs cause less drowsiness[31] and may, therefore, mitigate the risk of unsafe driving (Appendix Table A1). Nevertheless, the magnitude of this decline is small, and none of the estimates across the four intervals are statistically distinguishable from one another.

[31] Consequently, manufacturers appear less likely to include driving-related restrictions—such as "Driving not allowed"—a trend that is evident among medications introduced from 1994 to 2017 (Appendix Table A1). Consistent with this trend, retail scanner data indicate a substantial rise in the proportion of spending on allergy drugs that do not prohibit driving—from 25.2% in 2012 to 45.6% in 2019 (Appendix Figure A9).

6. Avoidance behaviors

Following the persistent negative effect of pollen on accidents discussed in the previous section, the next natural question is whether this effect already reflects people's engagement in avoidance behavior. If people do indeed engage in avoidance behavior *and* if such behavior proves effective, we may be understating the true magnitude of pollen-induced accidents, which would have occurred in the absence of such behavioral responses.

During our sample period, both forecasts and real-time pollen information were widely available via television, newspapers, and various mobile phone apps, giving people ample information and time to adopt avoidance behaviors if they wished. Several inexpensive and effective methods to reduce the risk of temporary pollen exposure and alleviate allergy symptoms are frequently mentioned on television and in other media. These methods include wearing particle-filtering masks and glasses, washing hands, avoiding clothing that easily attracts pollen, taking medication, and refraining from going outdoors (Japan Society of Immunology and Allergology in Otolaryngology 2021).

6.1. Conceptual framework

Here, we present a simple framework for considering the role of avoidance behaviors. Let us assume that $Accidents = f(Sick, Avoid)$, where the number of accidents is a function of sickness level ($Sick$) and avoidance behaviors ($Avoid$), or what Deschênes et al. (2017) refer to as "defensive investment." Given that the sickness level is influenced by ambient pollen concentration ($Pollen$) and avoidance behavior, i.e., $Sick = g(Pollen, Avoid)$,[32] substituting it yields the following equation:

$$Accidents = f(Pollen, Avoid)$$

Then, the total derivative can be written as follows (Moretti and Neidell 2011; Neidell 2009; Deschênes et al. 2017):

$$\underbrace{\frac{dAccidents}{dPollen}}_{\text{“behavioral” effect}} = \underbrace{\frac{\partial Accidents}{\partial Pollen}}_{\text{“biological” effect}} + \underbrace{\frac{\partial Accidents}{\partial Avoid}\frac{\partial Avoid}{\partial Pollen}}_{\text{effect of avoidance behaviors}}, [2]$$

where the "behavioral" effect (what we have estimated so far) of pollen on accidents consists of the "biological" effect of pollen (the first component of the right-hand side (RHS) variable) *and* the effect of avoidance behavior (the second component of the RHS variable). The latter is the

[32] More precisely, the level of sickness is a function of the dose of pollen one is exposed to, $Sick = g(Dose)$, and the dose is determined by the ambient pollen concentration ($Pollen$) and avoidance behavior ($Avoid$), i.e., $Dose = h(Pollen, Avoid)$. Substituting this into the first equation gives $Sick = g(Pollen, Avoid)$, as shown in the main text.

product of the marginal return to avoidance behavior $\left(\frac{\partial Accidents}{\partial Avoid} < 0\right)$ and the magnitude of avoidance behavior in response to pollen levels $\left(\frac{\partial Avoid}{\partial Pollen} > 0\right)$. Because the second component of the RHS variable is supposed to be negative, the total derivative, which already incorporates avoidance behavior, is *smaller* (i.e., underestimated) than the desired partial derivative.[33]

Among the many avoidance behaviors, we specifically examine two types that can be observed using existing data, as complete data on these behaviors are typically not available (Deschênes et al. 2017). First, using retail scanner data, we examine the purchase of products that protect against seasonal allergies, such as medications and masks. Second, using cellphone mobility records, we examine whether people, including allergy sufferers, curtail outdoor activities, which mainly reduces the risk of outdoor accidents. Further, staying indoors limits the possible infiltration of pollen and thus simply averts the onset of symptoms; because pollen grains are relatively large (≈30 μm) compared to much smaller particles, such as $PM_{2.5}$, they are less likely to enter homes if windows and doors are properly closed. In the following, we investigate the extent of these two types of selective avoidance behavior ($\frac{\partial Avoid}{\partial Pollen}$) in our context.[34]

6.2. Purchase of allergy products

Data—. We use retail scanner data, referred to as the "Quick Purchase Report" (QPR), provided by Macromill, Inc., a marketing firm that possesses one of the largest research panels on consumer purchasing behavior in Japan (Kuroda 2022). The QPR collects data from approximately 30,000 monitors to construct a nationally representative panel dataset.[35] These monitors scan all bar-coded items they purchase daily, providing information on the name and code, price, and quantity of products bought. Additionally, it incorporates certain demographic details about the monitors, such as zip code, age, gender, family structure, and income category, which are updated annually. We compare the key features of the widely used Nielsen Homescan Panel for the United States with those of the QPR and find that the two datasets are highly comparable (Appendix Table E1). Both are nationally representative household-level consumer

[33] For example, Neidell (2009) finds that the "reduced form" effect of ozone for the elderly and children is 40% and 160% smaller, respectively, than the purely "biological" effect.
[34] Purchasing allergy products corresponds to the $Avoid$ term in $Sick = g(Pollen, Avoid)$, which lowers the level of illness and thus *indirectly* reduces the risk of accidents. By contrast, limiting outdoor activities mainly corresponds to the $Avoid$ term in $Accidents = f(Sick, Avoid)$, which *directly* reduces the likelihood of outdoor accidents (Heft-Neal et al. 2023).
[35] QPR monitors are selected in each region to represent the gender, age group, and family structure (marital status and presence of cohabitants) of the country. To maintain data quality, if unusual scans are detected or if scans are not observed for several weeks, the monitor is replaced by another monitor with similar characteristics. Thus, the number of active QPR monitors at any given time is maintained at approximately 30,000, and the total number of unique QPR monitors during our sample period is 70,795.

panels collected using Homescan technology and contain similar purchase information, including online transactions.[36]

We extract purchase records for three items: allergy-related medications, allergy-related eye drops, and masks.[37] The dataset comprises over 28 million individual-day observations, encompassing days both with and without purchases, spanning from February to May for the years 2012 to 2019. To accommodate the potential for stockpiling these products, we aggregate the data to the person-week level.[38] See Appendix Table E2 for the sample's summary statistics.

Several limitations of this dataset merit acknowledgment. First, while we monitor purchases of over-the-counter (OTC) medications (e.g., antihistamines and decongestants), prescription medications are not tracked.[39] Second, individuals may purchase these goods in advance of the pollen season or use leftover medication from prior seasons. Last, information regarding actual usage is unavailable, a common issue across all retail scanner data.

Results—. We find that weekly spending on allergy-related products rises steadily with higher average daily pollen levels. This pattern holds for both overall allergy spending and specific categories, such as medications, eye drops, and masks, each demonstrating a roughly linear relationship with logged pollen counts (Appendix Figure E1).

Table 4 reports estimates from a variant of equation [1] modified to weekly data. Column (1) demonstrates that a 10% increase in pollen counts leads to an additional \$4.40 (in 10^{-3}\$) in weekly spending on allergy products. At the national level, this translates to \$9.6 million (= $4.40\times10^{-3}\times120/7\times127.4$ million) per season, where 120 days represent a typical pollen season, and 127.4 million is the total population of Japan. Columns (2)–(4), which describe individual products, indicate that the largest increase (relative to the mean) comes from purchases of medicines.[40]

Supplementary analysis—. We also complement the above analysis by using Google Trends/Twitter data containing the keywords "mask," "air purifier," and leading brand names of allergy medications in Japan to examine whether people are searching for information about specific protective products. Previous studies show that such searches closely track actual

[36] The main differences concern product coverage and detail—while the Nielsen data include some manually reported non-barcode items and coupon/deal flags, the QPR data cover only JAN-coded goods and lack coupon information. However, because our analysis focuses on drug purchases, which are very likely barcode-based, the two datasets can be regarded as essentially equivalent for our purposes.

[37] While medications are intended to relieve symptoms (e.g., stop a runny nose), they may not always reduce the risk of accidents because they cause drowsiness in some people (i.e., the sign of $\frac{\partial Accidents}{\partial Avoid}$ is unclear for them).

[38] The weekly analysis provides larger estimates than would be implied by a linear scaling of the daily estimate (not shown).

[39] According to the latest government statistics (MHLW 2022), expenditure on OTC drugs and prescription drugs for allergies (including SAR) was \$0.39 and \$1.73 trillion, respectively, suggesting that OTC drugs account for about 20% of the total expenditure on allergy drugs. An exchange rate of 100 yen/\$ is used for simplicity.

[40] These results are consistent with previous studies documenting a similar relationship between pollen counts and OTC allergy medication sales in New York City, United States (Ito et al. 2015) and Japan (Kuroda 2022).

purchases (Goel et al. 2010). Compared to purchase data, these measures are more likely to capture contemporaneous behavior, which should be more directly affected by daily fluctuations in pollen counts. Consistent with this expectation, we find a strong positive relationship between pollen counts and both search activity and tweet volume for these keywords (Appendix Figure F1).

6.3. Avoiding going out

Data—. We use cellphone mobility records, referred to as "Mobile Spatial Statistics" (MSS), provided by NTT DOCOMO, Inc., Japan's largest mobile phone carrier. MSS provides hourly population estimates for 500×500-meter mesh cells across Japan, based on location data from approximately 85 million NTT DOCOMO users (as of March 2022), out of Japan's total population of 127 million (Terada et al. 2013).[41] While physical mobility data have received considerable attention in the social sciences since the onset of the COVID-19 pandemic (e.g., Google's COVID-19 Community Mobility Reports), such data have not yet been extensively utilized for studying avoidance behavior in response to environmental stressors (see Burke et al. 2022).

One potential concern is whether population estimates derived from cell-phone data accurately reflect actual human mobility. To evaluate this, following Neidel (2009), we obtain daily admission data from 2008–2019 for three major zoos operated by the Tokyo Metropolitan Government—namely, Ueno Zoo, Tama Zoological Park, and Inokashira Park Zoo—and compare these counts with cell-phone–based population estimates for the 500×500-meter mesh cells adjacent to each zoo's entrance.[42] Across all three facilities, the logged daily attendance is highly positively correlated with the logged daily population estimates from cellphone mobility records, indicating that the cell-phone–based measure closely tracks real movement (Appendix Figure G1).[43]

Our primary mobility metrics capture the estimated population of a mesh with the highest number of customer service establishments in the municipality, aiming to identify bustling areas (e.g., business districts, shopping, and dining areas) that are more likely to reflect the population engaged in outdoor activities. We opt for the estimated population at 2 p.m. as commercial area

[41] Given the sample's representativeness and the long-time span, this dataset has been widely used, especially for measuring human mobility during the COVID-19 pandemic (e.g., Kondo 2021; Kuroda et al. 2025).
[42] To ensure consistency with the subsequent analysis, we employ the mobility data measured at 2 p.m.
[43] Although geographical variation is limited because all three facilities are located within Tokyo, we find that admissions decline on days with higher pollen levels. However, these results should be interpreted with caution, considering the limited spatial variation in exposure (based on three monitoring stations) and the limited representativeness of the sample (Appendix Figure G2 and Table G2).

populations typically peak around this time (Seike et al. 2015).[44] We collapse the estimated population at the emergency response unit level by averaging across all municipalities within the unit for the period from February 2014 to May 2019. We consider this measure a proxy for engaging in outdoor activities, termed "outdoor population" hereafter. See Appendix G for details on the data construction of our mobility metrics.[45]

Before examining the relationship between pollen load and mobility metrics, we aim to verify the effectiveness of limiting outdoor activities in reducing the risk of accidents.[46] Specifically, we regress the number of accidents (our primary outcome) on our mobility metric using the same FEs and controls as in equation [1] (excluding the logged number of pollen counts). We find that outdoor population is highly positively correlated with the number of accidents, indicating that reducing outdoor activity can meaningfully lower accident risk ($\frac{\partial Accidents}{\partial Avoid} < 0$), consistent with Heft-Neal et al. (2023), as presented in Appendix Table G2.

Results—. We find no clear association between logged pollen counts and logged outdoor population on weekdays; however, on weekends, the relationship becomes modestly negative, suggesting that individuals engage in some avoidance behavior by staying indoors when pollen levels are high (Appendix Figure G3).

Table 5 presents estimates from equation [1], with the outcome being the logged outdoor population. Columns (1) and (2) indicate negligible and statistically insignificant estimates for all days and weekdays. By contrast, column (3) reveals that people tend to avoid crowded areas on high pollen weekends when they have more flexibility in canceling or rescheduling non-urgent trips. The elasticity of outdoor population with respect to pollen counts appears non-trivial: –0.0021 (p-value<0.01), indicating that a 10% increase in pollen concentration results in a 0.021% decrease in outdoor population.[47]

We examine heterogeneity using two key demographic characteristics—namely, age and sex—and find minimal differences by gender (Appendix Table G4). By contrast, older individuals do not seem to reduce outdoor activities even on weekends, consistent with the larger pollen-related effects on accidents observed in Figure 9. This pattern suggests scope to promote

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[44] We also explore alternative methods for constructing measures of outdoor mobility, specifically focusing on the disparity between the daytime (2 p.m.) and nighttime (4 a.m.) populations, as well as the ratio of daytime to nighttime populations. The results are qualitatively similar (not shown), primarily because nighttime population remaining relatively stable over time, therefore adds little information after controlling for unit fixed effects.

[45] As in other studies of physical activity, we cannot distinguish between two possibilities for staying indoors: people may be extremely ill and need to stay home, or they may show some form of avoidance.

[46] Similarly, we cannot test whether the purchase of allergy products effectively reduces accidents because the regional sampling units in the retail scanner data are only ten divisions (albeit nationally representative) and do not correspond to the detailed regional units in the ambulance records (N= 705).

[47] Estimates for other weather covariates align with expectations: Outdoor population rises with higher temperatures and falls with stronger winds and longer duration of darkness (Appendix Table G3).

avoidance behaviors within this subgroup.[48]

In summary, our findings suggest that people indeed engage in avoidance behaviors by purchasing allergy products and limiting outdoor activities, particularly on weekends. These behaviors might lead to an underestimation of the true impact of pollen-induced accidents if they prove effective.

7. Projecting damages due to climate change

This section projects the estimated effects forward to predict increases in allergy-induced accidents under future climate change.[49] Table 6 summarizes the projected damages based on the "business as usual" scenario (RCP 8.5), which predicts a 4.1°C increase in summer temperatures in Japan from 2076 to 2095 (MEXT and JMA 2020). According to the relationship between summer temperature and pollen counts (panel A of Figure 1), this temperature rise could result in an additional daily pollen count of 686 grains/m^3 (= 167.4×4.1), corresponding to a 0.529 increase in logged pollen counts from the mean of 984 grains/m^3. We then multiply the estimates from panel A of Figure 8 for each severity level by 0.529, then by 120 (days per pollen season), and finally by 127.4 (the total population) to calculate the additional annual accidents, as shown in row (1). Row (1) indicates that a 4.1°C increase in the mean summer temperature is expected to raise the number of pollen-induced deaths/fatalities, severe, moderate, and minor accidents by 30, 216, 541, and 1,036, respectively, totaling 1,823 additional annual accidents.

We convert additional accidents into monetary terms by multiplying the resulting accident counts in row (1) by the average accident costs from Bünnings and Schiele (2021) in the United Kingdom, as reported in row (2).[50] Row (3) displays pollen-induced accidents resulting in fatal, severe, moderate, and minor injuries, corresponding to actual monetary costs of $96.3 million, $79.1 million, $20.6 million, and $39.6 million, respectively. This results in a total annual societal cost of $236 million, as shown in row (4).[51] Interestingly, this figure far exceeds the budget for the Japanese Forestry Agency's pollen reduction program, which is currently $1.1

[48] By contrast, when examining the purchase of allergy products, we find no meaningful differences in pollen's effect across age or gender groups (Appendix Table E3).

[49] We acknowledge that we are making two strong assumptions here: (i) the level of protective technologies remains the same; (ii) the marginal treatment effect of an unanticipated "weather" shock documented so far is identical to the marginal effect of an anticipated "climate" shift. Previous studies have taken a similar approach when projecting the impact of these gradual changes on income (Deryugina and Hsiang 2014), mortality (Deschênes and Greenstone 2011), amenity values (Baylis 2020), and other outcomes.

[50] We determine the expected additional costs to be $3.2 million for fatal accidents (those resulting in death), $365,000 for accidents resulting in serious injury, and $38,000 for accidents resulting in both moderate and minor injuries (Bünnings and Schiele 2021). For simplicity, an exchange rate of 1.5 $/£ is used. Unfortunately, to the best of our knowledge, there are no appropriate estimates of accident costs at each severity level in Japan.

[51] Panel B of Table 6, which uses the number of days with temperatures above 30°C in the previous year (panel B of Figure 1), yields estimates of social costs that are about 40% larger than those in panel A of Table 6, which uses maximum temperature.

million (Forest Agency 2021).[52]

We acknowledge that our simple damage projection calculation is likely a conservative estimate because (i) we exclude potential extension of the pollen season driven by hotter summers, (ii) we limit the analysis to approximately four months of peak pollen season, (iii) we cannot capture accidents occurring at both extremes of severity (i.e., minor cases not requiring ambulance transport and immediate deaths), and (iv) we use a relatively conservative value of a statistical life (Bünnings and Schiele 2021) rather than a more commonly used value.[53]

Finally, to the extent that expenditures on allergy products can be considered defensive expenditures rather than just another health expenditure (i.e., a transfer from individuals to firms), such expenditures should be included in the social cost (Deschênes et al. 2017). Based on the calculation in Section 6.2, a 0.529 (instead of 0.1) increase in recorded pollen counts because of elevated temperatures leads to \$50.8 million (= \$9.6 million ×0.529/0.1) in additional spending on allergy products. This figure is not trivial compared to the \$236 million associated with pollen-induced accidents calculated above, suggesting the empirical importance of defensive spending.

8. Discussion and Conclusion

This study represents the first assessment of the impact of pollen exposure on accident likelihood, using Japanese archived ambulance records spanning from 2008 to 2019. We find that exposure to heightened pollen levels escalates the incidence of all accident types. Our findings align with established clinically based studies, which have documented the adverse cognitive effects of pollen exposure. The long-term implications of these effects have not been previously evaluated in real-world settings, except in the realm of children's academic performance. Moreover, the nearly ubiquitous effect of pollen exposure across various observed demographics, coupled with its relatively enduring effects over time, suggests a potentially generalizable underlying mechanism linking pollen exposure to accidents across contexts.

Our analysis of internet search activities and social media posts for pollen-related topics indicates that individuals have a good awareness of daily pollen levels. Additionally, further analysis of retail scanner data and cellphone mobility records reveals that people actively engage in avoidance behaviors. These behaviors include purchasing products like medications and masks to safeguard against seasonal allergies, and in some cases, curtailing outdoor activities during weekends to mitigate the risk of pollen exposure and associated allergy symptoms.

[52] Because of the growing demand for government intervention, the current administration has decided to increase it to \$61 million in fiscal year 2024.

[53] For example, the central estimate of the value of statistical life used by the Environmental Protection Agency in the United States is \$9.8 million in 2021, and Smith (2016) similarly uses \$4 million to \$10 million per fatality, both of which are larger than the \$3.2 million figure we use.

These results suggest that reliance on individual self-protection alone may fall short of mitigating pollen-related harm. This study is, to the best of our knowledge, the first to document a causal relationship between pollen exposure and accident risk in a real-world setting; hence, individuals may not fully appreciate this risk or incorporate it into their decision-making, resulting in suboptimal avoidance behavior.[54] Accordingly, clearly disseminating information about these risks—including the evidence presented in this study—constitutes a critical first step, particularly considering the abundance of pollen-related information already available in various forms in Japan.[55]

Furthermore, considering the negative externalities associated with accidents and the substantial social costs of pollen-induced incidents, additional government involvement may be warranted. Broadly, government interventions can be classified into the following two types: *ex-post* interventions (adaptation) and *ex-ante* interventions (mitigation). Ex-post measures aim to reduce individuals' exposure to pollen or lessen the harm associated with exposure, whereas ex-ante measures target the source of pollen "production," such as trimming pollen-emitting trees or replacing them with low-pollen-emitting varieties.

A feasible, rapidly implementable ex post intervention is the provision of medication subsidies. Although recently released allergy medications tend to contain fewer ingredients that cause drowsiness (Appendix Table A1), time-series patterns of spending on seasonal allergy drugs (Appendix Figure A8) reveal that such medications accounted for less than 50% of total allergy-related expenditures in 2019. This suggests substantial scope for increasing the use of less drowsy medications by offering subsidies or reducing prices.[56]

Another promising ex-post strategy is to launch a public information campaign to reduce exposure to high pollen levels, for example, by issuing pollen alerts to notify the public when pollen dispersal is high. On days with an active alert, the government could provide standardized guidance to firms and the public on appropriate responses. For the public, this guidance might include behavioral recommendations, such as wearing masks, using air purifiers, taking public transportation, and avoiding nonessential outdoor activities. As older adults—who are at greater risk of pollen-related accidents—are less likely to engage in avoidance behaviors, providing

[54] Thus, the current state of protective behavior is unlikely to reflect people's revealed preferences, which already incorporate potential risk (Leard and Roth 2019).
[55] This distinction is important for policy design. When access to information is limited, governments should focus on expanding the dissemination of pollen information (Barwick et al. 2024; Jha and Nauze 2022). When access is already widespread, as in our setting, the challenge instead lies in capturing attention. In such cases, policy should emphasize more effective ways to raise awareness of risks and encourage behavioral change. Prior studies show that smog and ozone alerts can successfully induce precautionary behaviors that reduce exposure (e.g., Anderson et al. 2022; Cutter and Neidell 2009).
[56] For example, Kohou Logistics (Tokyo), a transportation firm, has distributed over-the-counter tablets and other medications at no cost to truck drivers affected by hay fever since fiscal year 2019 (Yomiuri Shimbun 2023). See also Inuma and Lee (2024) "Japan's answer to seasonal allergies: A subsidized tropical escape" in the Washington Post.

timely alerts along with clear recommendations seems to be a particularly effective way to reduce accidents.

Furthermore, governments may issue guidelines encouraging firms to implement adaptive measures for their employees, thereby helping mitigate productivity losses associated with pollen exposure. For example, on days when a pollen alert is in effect, firms could allow temporary remote work or grant short-term sick leave to employees with clinically significant symptoms. Our findings indicate that individuals substantially curtail outdoor activities only on weekends, suggesting a latent willingness to avoid high-pollen environments during weekdays as well. The primary barrier may be the opportunity cost of missing work, highlighting the importance of employer-supported flexible work arrangements in enabling effective adaptation.

Ex-ante interventions instead aim to curb pollen production at the source.[57] A negative externality emerges when pollen-producing trees are planted for industrial or commercial reasons by decision-makers who do not bear the resulting health damages. This misalignment provides a clear rationale for government intervention. One approach is to mandate the use of low-pollen tree species and levy a surcharge on planting agents and landowners who do not comply, thereby inducing them to internalize the social costs of pollen emissions.[58]

In sum, noteworthily, the social costs that we estimate likely represent only the *tip of the iceberg* of the broader societal burdens associated with rising pollen counts. Although we remain agnostic regarding the underlying mechanisms, to the extent that pollen exposure impairs cognitive function, any daily activity requiring normal cognitive alertness and decision-making capabilities may be affected. Therefore, quantifying these potential damages is essential for developing a comprehensive understanding of the full social costs associated with elevated pollen concentrations.

[57] However, implementing these measures may take considerable time and entail costs associated with reductions in forests' water conservation functions, including water storage, flood mitigation, and water purification. Consequently, ex-post interventions can function as effective second-best remedies in the short run.
[58] For example, Germany has issued guidelines encouraging the use of low-allergenic tree species (Bergmann et al. 2025)

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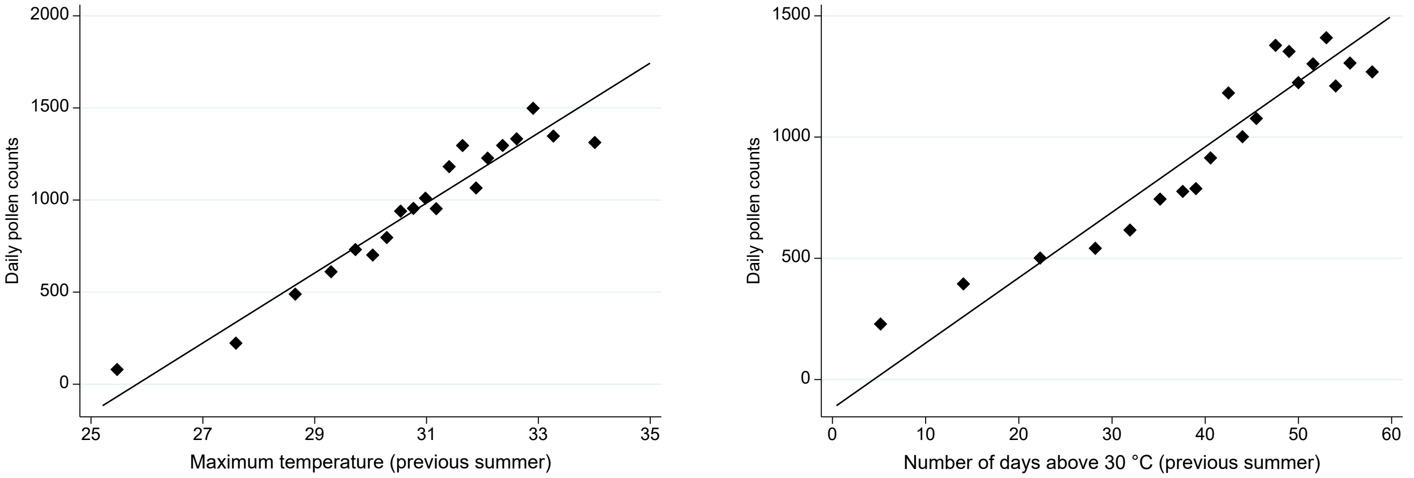
Figure 1—Pollen count and temperature from the previous summer

A. Maximum temperature of the previous year

B. Number of days above 30°C in the previous year

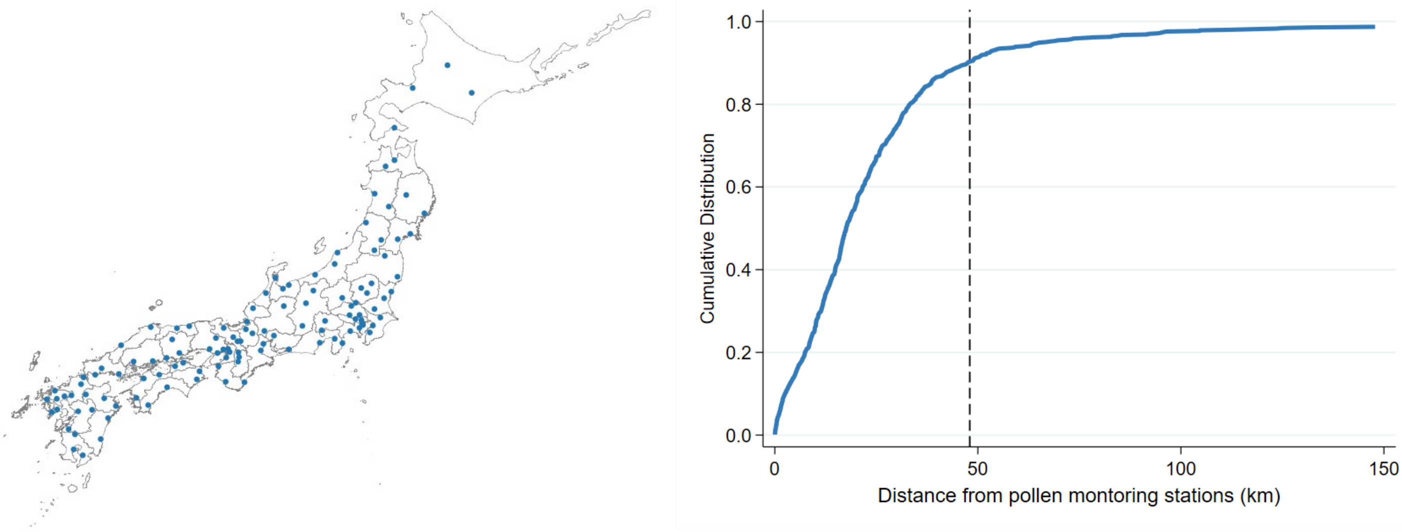


Notes: The sample comprises station years (N=1,440) from all pollen monitoring stations (N=120) over the period 2008 to 2019 (12 years). The graphs display binscatter plots illustrating the relationship between the average (24-hour cumulative) daily pollen counts (grains/m^3) from February to May (on the *x*-axis) and the average maximum temperature (in °C) in panel A, and the number of days the temperature exceeded 30°C in July and August of the previous summer in panel B (on the *x*-axis). These relationships are shown after controlling for the fixed effects of the pollen monitoring stations. In panel A, the slope is 167.4 (t-stats=11.16), indicating that a one-degree increase in the maximum temperature in the previous summer corresponds to a 167.4 grains/m^3 increase in daily pollen counts. Similarly, in panel B, the slope is 23.7 (t-stats=11.18), suggesting that for every ten additional hot days above 30°C in the previous summer, daily pollen counts increase by 237 grains/m^3. The mean and median daily pollen counts from February to May during 2008 to 2019 across 120 monitoring stations are 955.6 and 712.5 grains/m^3, respectively.

Figure 2—Pollen monitoring stations

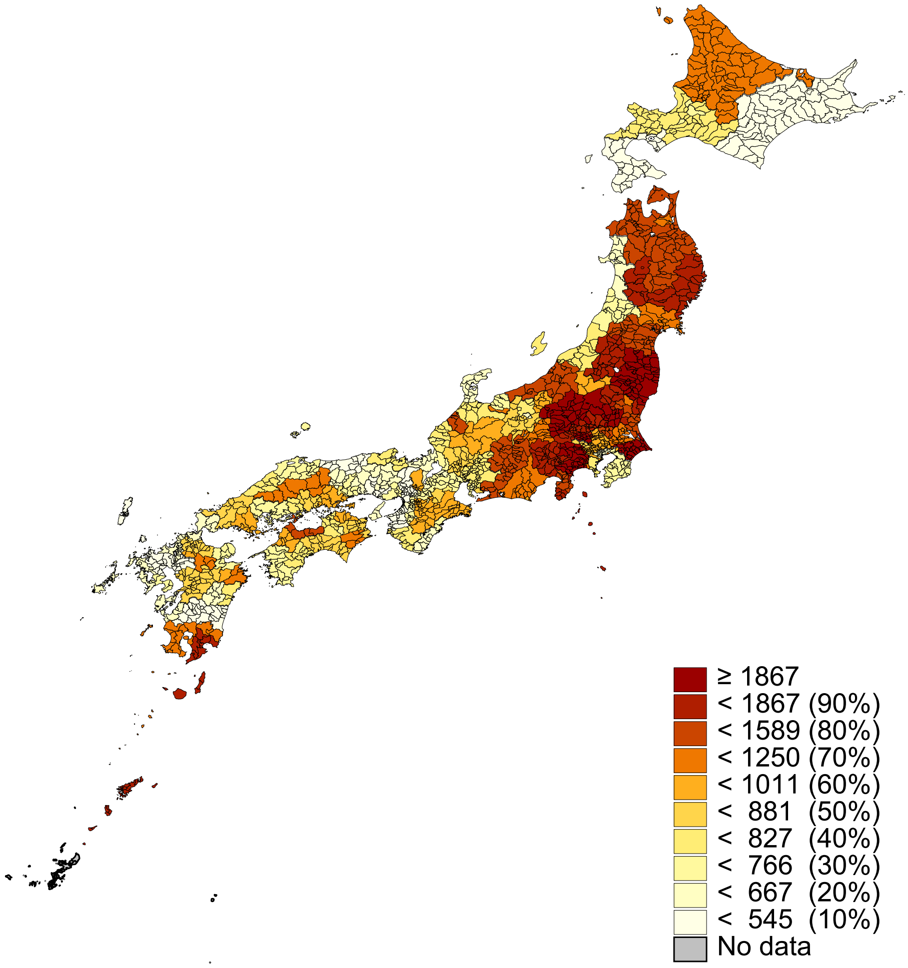
A. Location of pollen monitoring stations

B. Distance to the pollen monitoring stations



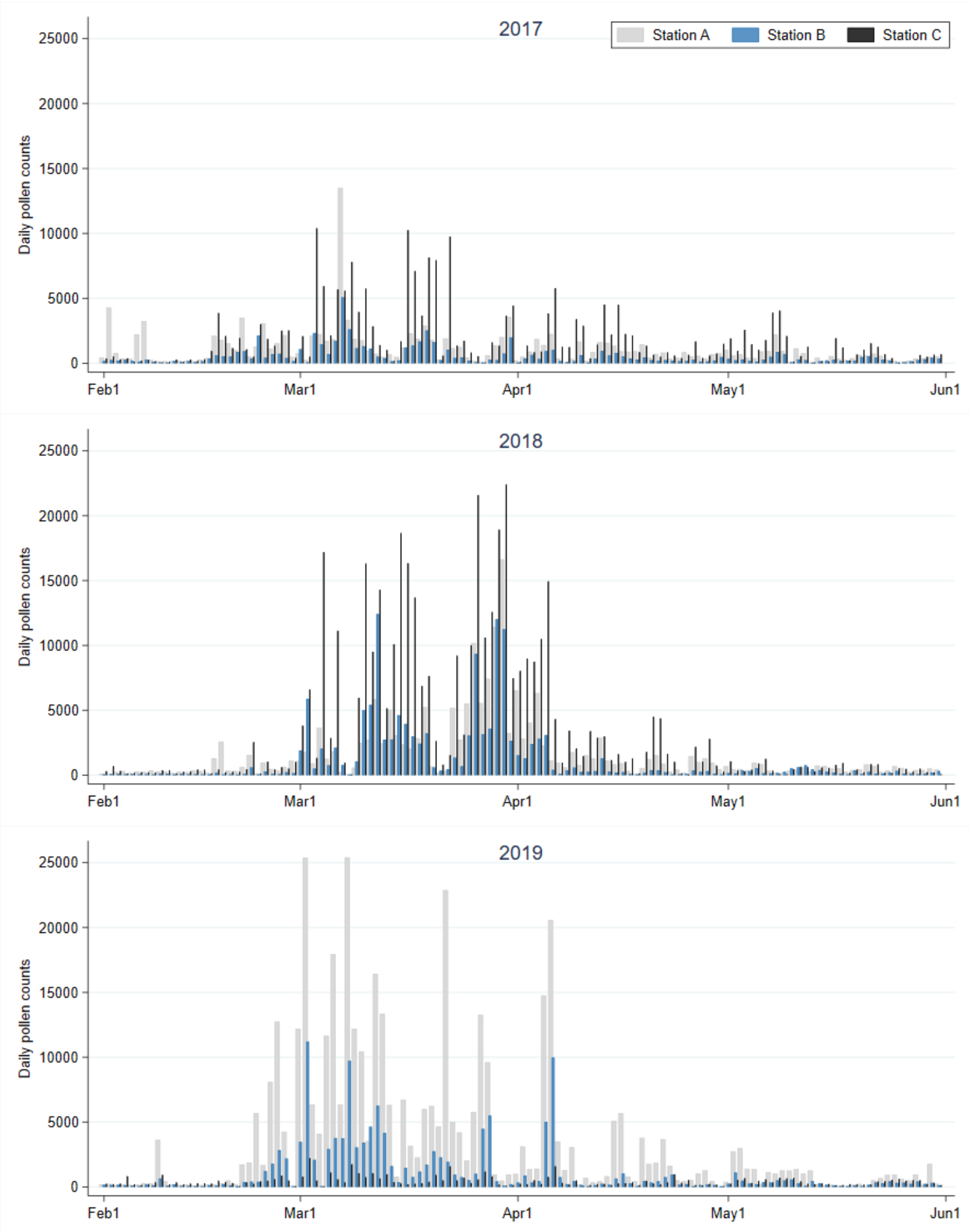
Notes: Panel A displays the locations of all pollen monitoring stations as of 2019. Japan hosts 120 pollen stations. On average, each of Japan's 46 prefectures has 2 to 3 stations, except for Okinawa. Due to its distinct climate, Okinawa, the southernmost prefecture, lacks any monitoring stations as pollen is not observed there. Panel B illustrates the cumulative distribution of the distance from the centroid of the units (N=705) to the nearest pollen monitoring station (N=120). The vertical dotted line represents 48 km (30 miles), a distance referenced by Chalfin et al. (2019). Notably, 90.2% of the stations (636 out of 705) fall within this threshold.

Figure 3—Spatial variation in pollen counts



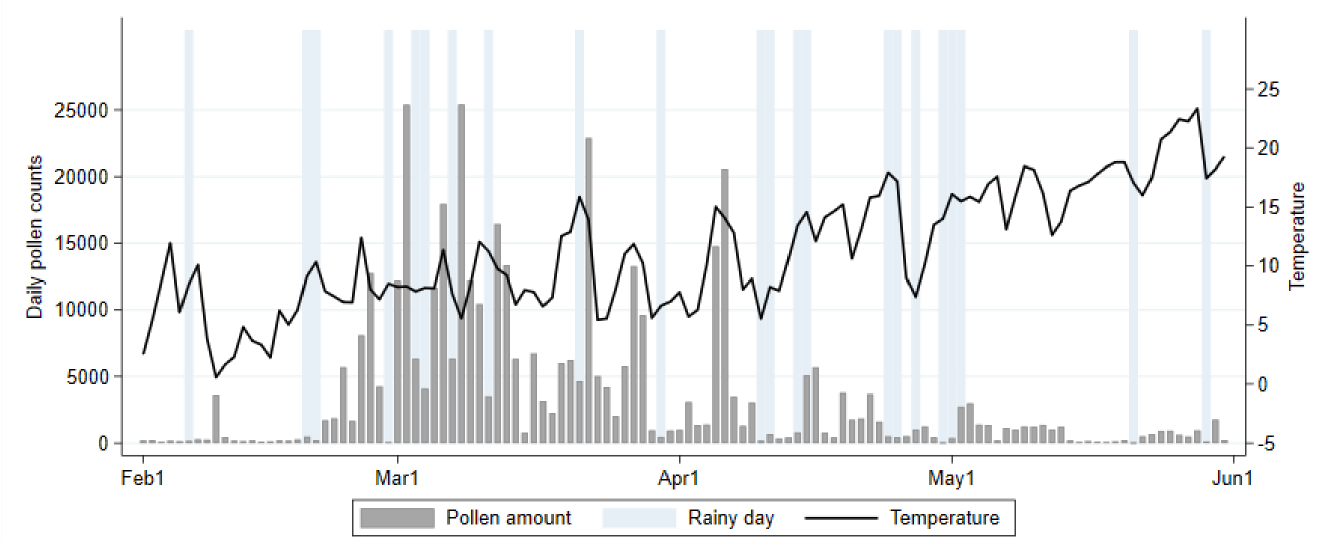
Notes: This figure presents the average pollen counts (grains/m^3) from 2008 to 2019 across municipalities. Notably, Okinawa Prefecture, the southernmost island in Japan with a distinct climate, lacks a pollen station due to minimal pollen observed.

Figure 4—Temporal variation in pollen counts from Ibaraki Prefecture



Notes: The graphs show daily variations in pollen counts (grains/m^3) from 2017 to 2019 at three monitoring stations in Ibaraki Prefecture, located northeast of Tokyo within the Kanto region (see Appendix Figure A2).

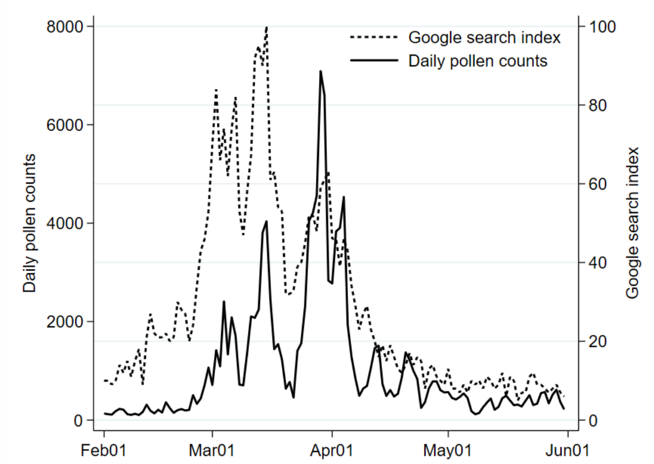
Figure 5—Daily pollen counts and weather conditions



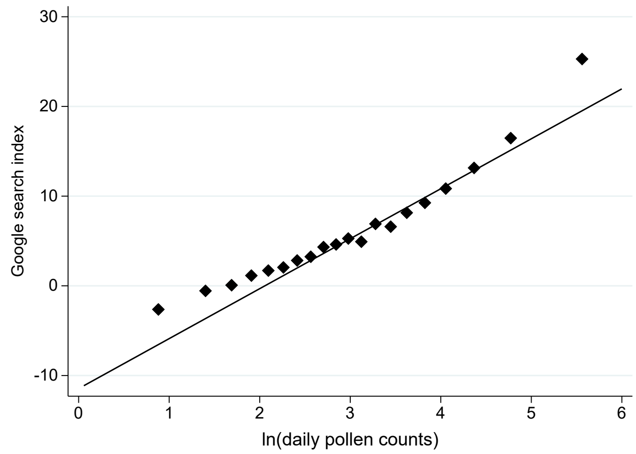
Notes: This figure extracts data from Station A in 2019 from Figure 4, supplements it with the average temperature, and color-codes days with any recorded precipitation.

Figure 6—Pollen and symptom-related Google search index

A. Time series

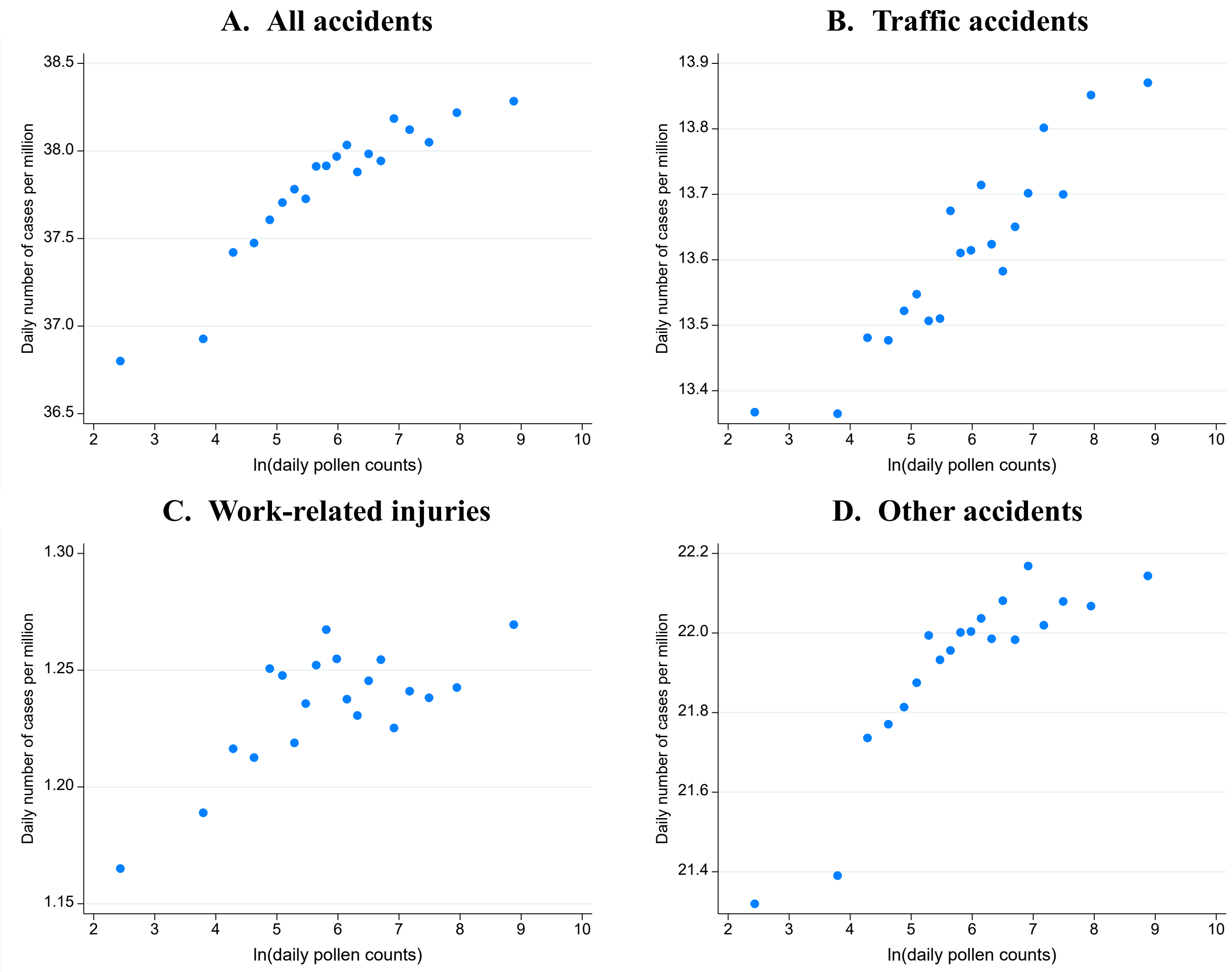


B. Binscatter plot



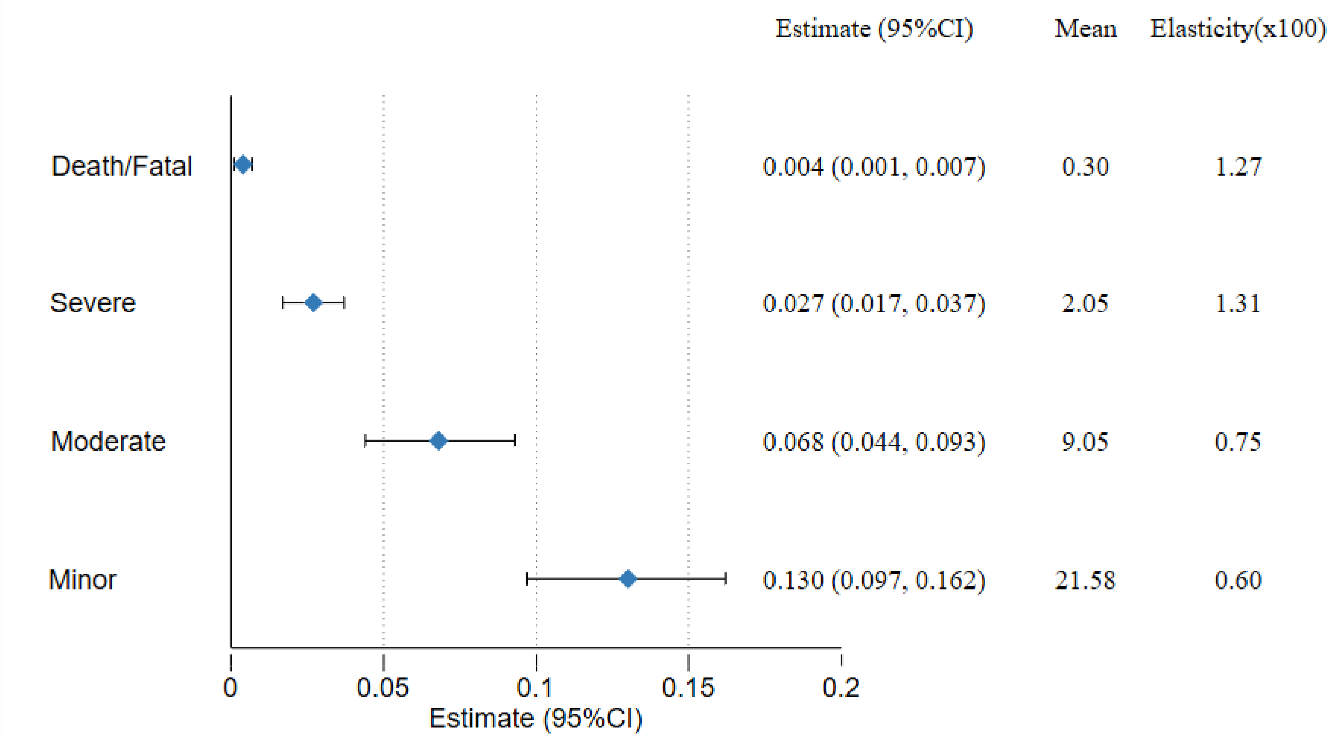
Notes: The sample is derived from Google Trends data, with observations at the prefecture-per-day level. Panel A illustrates time-series patterns of average daily pollen counts (grains/m^3) and the Google search index for symptom-related keywords in 2018 on a national scale. Symptom-related keywords include "runny nose," "nasal congestion," "sneezing," and "itchy eyes." June is omitted because only 4 stations in Hokkaido (Japan's northernmost island) were still active in June. Panel B displays binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the x-axis) and the Google search index for the mentioned keywords (on the y-axis), after controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population in each prefecture per year. See Appendix Figure B1 for similar plots regarding pollen allergy-related keywords, exhibiting similar patterns.

Figure 7—Pollen and the number of accidents



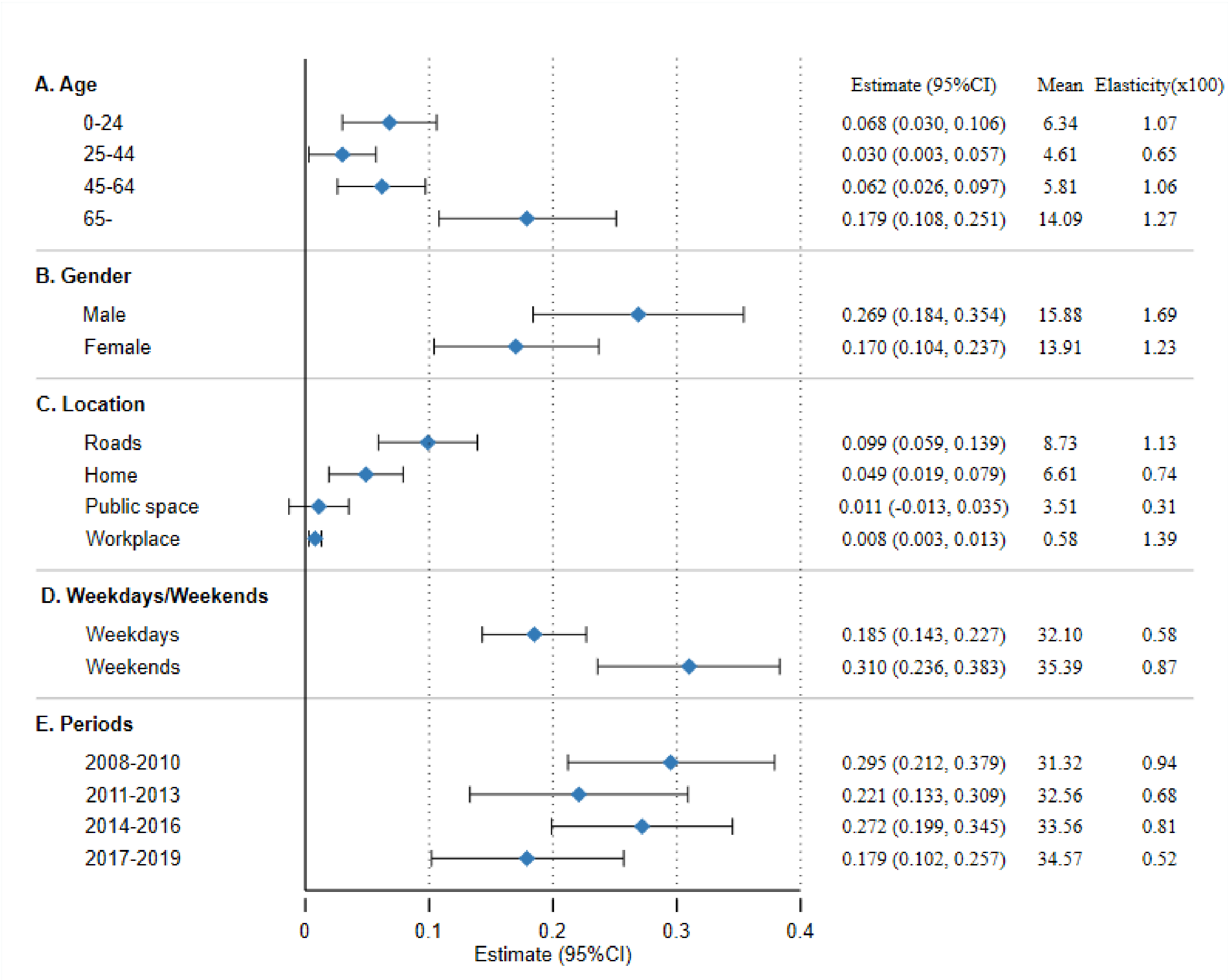
Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 units are available. The graphs display binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the x-axis) and the daily cases per million people for all accidents (panel A) and specific accident types in panels B to D (on the y-axis): traffic accidents (panel B), work-related injuries (panel C), and other accidents (panel D), after controlling for unit, month-by-year, month-by-prefecture, and day-of-week FEs, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. The shares of traffic accidents (panel B), work injuries (panel C), and other accidents (panel D) are 37.6%, 3.5%, and 55.8%, respectively. Estimates are weighted by the population in each unit.

Figure 8—Treatment effects by severity



Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. The plots exhibit estimates and 95% confidence intervals of treatment effects of logged daily pollen counts from equation [1]. Standard errors are clustered at the pollen monitoring station level. The dependent variables are the number of daily cases per million people categorized by severity level. Severity is assessed by physicians upon hospital admission, with "severe" accidents requiring over three weeks of hospitalization and treatment, "moderate" necessitating hospitalization under three weeks, and "minor" not requiring hospitalization. The mean represents the daily accident cases per million population. Elasticity (x100) measures the change in outcome associated with a 100% increase in pollen counts divided by the mean times 100. Estimates are weighted by the population in each unit.

Figure 9—Other heterogeneous treatment effects



Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. The plots exhibit estimates and 95% confidence intervals of heterogeneous treatment effects of logged daily pollen counts from equation [1]. Standard errors are clustered at the pollen monitoring station level. The dependent variables are the number of daily accident cases per million people using all accident data. The mean represents the daily cases per million population. Elasticity (x100) measures the change in outcome associated with a 100% increase in pollen counts divided by the mean times 100. Estimates are weighted by the population in each unit.

Table 1—Summary statistics

Variables	**Share within *category***	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
A. Outcomes (per 1,000,000 per day)						
All accidents		970,309	33.03	28.23	0	5,091
Type: Traffic accidents	*37.6%*	970,309	12.41	16.09	0	5,091
Type: Work-related injuries	*3.5%*	970,309	1.15	3.87	0	1,367
Type: Sports injuries	*2.6%*	970,309	0.86	3.24	0	1,195
Type: Fire accidents	*0.5%*	970,309	0.17	2.10	0	2,612
Type: Other accidents	*55.8%*	970,309	18.44	17.77	0	2,447
Severity: Death/Fatal	*0.9%*	970,309	0.30	2.11	0	943
Severity: Severe	*6.2%*	970,309	2.05	6.07	0	1,572
Severity: Moderate	*27.4%*	970,309	9.05	11.90	0	1,958
Severity: Minor	*65.4%*	970,309	21.58	20.65	0	4,570
Ages: 0–24 years	*20.5%*	970,309	6.34	9.44	0	2,112
Ages: 25–44 years	*15.0%*	970,309	4.61	7.64	0	2,186
Ages: 45–64 years	*18.8%*	970,309	5.81	8.90	0	2,637
Ages: 65 years and older	*45.7%*	970,309	14.09	15.98	0	2,695
Gender: Male	*53.3%*	970,309	15.88	17.55	0	4,769
Gender: Female	*46.7%*	970,309	13.91	15.82	0	2,366
Location: Roads	*44.9%*	970,309	8.73	12.66	0	198
Location: Home	*34.0%*	970,309	6.61	9.90	0	82
Location: Public space	*18.1%*	970,309	3.51	5.73	0	51
Location: Workplace	*3.0%*	970,309	0.58	1.14	0	58
B. Regressors (per day)						
Pollen counts (grains/m^3)		970,309	984.34	2135.26	0	55,104
Logged (Pollen counts)		970,309	0.16	0.43	0	10
Precipitation (mm)		970,309	11.90	6.14	0	28
Average temperature (℃)		970,309	2.93	1.39	0	16
Average wind speed (m/s)		970,309	10.48	1.28	7	13
Darkness (hours)		852,948	2.20	2.16	0	521
SO_2 (ppb)		846,719	6.14	10.07	0	307
NO_2 (ppb)		846,659	15.11	9.60	0	88
CO (0.1ppm)		848,798	4.02	1.84	0	61
OX (ppb)		850,847	36.76	11.51	0	120
PM_{10} (µg/m^3)		850,577	20.04	11.14	0	299

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level. A total of 705 emergency response units are available, with population weights applied. The sum of shares within each category should equal 100%. Pollution data have been available since 2009.

Table 2—Main results: Accidents

	A. All accidents	B. By type				
		Traffic accidents	Work-related injuries	Sports injuries	Fire accidents	Other accidents
	(1)	(2)	(3)	(4)	(5)	(6)
ln(pollen counts)	0.231***	0.079***	0.012***	0.007**	0.006***	0.127***
	(0.020)	(0.012)	(0.002)	(0.003)	(0.002)	(0.016)
R-squared	0.46	0.24	0.06	0.08	0.00	0.37
N	970,309	970,309	970,309	970,309	970,309	970,309
N of units	705	705	705	705	705	705
N of clusters	120	120	120	120	120	120
Mean of dep. var	33.03	12.41	1.15	0.86	0.17	18.44
Elasticity (x100)	0.70	0.64	1.04	0.81	3.53	0.69
Share	*100%*	*37.6%*	*3.5%*	*2.6%*	*0.5%*	*55.8%*
Unit FE	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X
Month-by-year FE	X	X	X	X	X	X
Prefecture-by-month FE	X	X	X	X	X	X

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. The dependent variable is the number of daily cases per million people for each type of accident. Estimates from equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. In addition to the fixed effects listed in the table, weather covariates (precipitation, temperature, wind speed), darkness, and logged population are included. Estimates are weighted by the population in each unit. The mean represents the number of daily accident cases per million population. Estimates are weighted by the population in each unit. Elasticity (x100) measures the change in outcome associated with a 100% increase in pollen counts divided by the mean times 100. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 3—Robustness: Accidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Pollen measures		Additional controls		Measurement errors		Others		
	Baseline	Weighted average of nearby three stations	Drop zero pollen observations	(1)+Add pollution	(1)+Add temperature & rain interactions	Units within 48 km of stations	Limit stations within 8 km of weather stations	Add 2016-2019 Tokyo	Unweighted	Collapse data at the weekly level
ln(pollen counts)	0.231***	0.234***	0.249***	0.220***	0.205***	0.229***	0.233***	0.216***	0.402***	0.213***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.020)	(0.020)	(0.024)	(0.023)	(0.066)	(0.036)
R-squared	0.46	0.46	0.46	0.47	0.46	0.48	0.37	0.46	0.33	0.85
N	970,309	970,309	962,255	814,578	970,309	872,227	733,552	970,789	970,309	147,066
Unit FE	X	X	X	X	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X	X	X	X	
Month-year FE	X	X	X	X	X	X	X	X	X	
Month-prefecture FE	X	X	X	X	X	X	X	X	X	
Year-prefecture FE										X
Week-unit FE										X

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level. A total of 705 emergency response units are available. Estimates from the variant of equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. Column (1) replicates the results from Table 2 (baseline) for ease of comparison. Column (2) employs daily pollen counts constructed by the inversely weighted average of three nearby stations as the main regressor. Column (3) excludes zero pollen counts (0.83%) and takes a logarithm without adding 1. Column (4) introduces air pollution covariates (SO_2, NO_2, CO, OX, PM_{10}) for the period spanning April 2009 to April 2019, if such data are available, and column (5) includes the full interaction of temperature and precipitation. Column (6) limits to units located within 48 kilometers of pollen monitoring stations. Column (7) limits the sample to observations linked to pollen stations located within 8 kilometers of weather stations. Column (8) includes data from Tokyo for the years 2016–2019. Column (9) employs unweighted ordinary least squares (OLS). Column (10) aggregates the data to the weekly level. All specifications include unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, weather covariates (precipitation, temperature, wind speed), darkness, and logged population, except for column (10), which includes year-by-prefecture and week-by-unit fixed effects. Estimates are weighted by the population in each unit. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 4—Avoidance behaviors: Purchasing allergy products

	A. Total	B. By category		
		Medications	Eye drops	Masks
	(1)	(2)	(3)	(4)
ln(pollen counts)	44.002***	24.521***	13.143***	6.429***
	(2.545)	(1.428)	(0.969)	(0.824)
R-squared	0.006	0.004	0.003	0.002
N	4,303,417	4,303,417	4,303,417	4,303,417
N of individuals	70,795	70,795	70,795	70,795
Mean of dep. var (in 10^{-3}\$)	295.78	109.94	103.41	82.52
Share	*100%*	*37%*	*35%*	*28%*
Municipality FE	X	X	X	X
Year-prefecture FE	X	X	X	X
Week FE	X	X	X	X

Notes: The sample is derived from retail scanner data from February to May for the period 2012 to 2019, with observations at the person per week level (N= 4,303,417). The dependent variable is the weekly expenditure (in 10^{-3} \$) for each allergy product. An exchange rate of 100 yen/\$ is applied. Estimates from the variant of equation [1] are reported with standard errors clustered at the pollen monitoring station level in parentheses. In addition to the fixed effects listed in the table, weather covariates (precipitation, temperature, wind speed), and darkness are included. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 5—Avoidance behaviors: Avoiding going out

Outcome: logged outdoor population

	A. All	B. By type of day	
		Weekdays	Weekends
	(1)	(2)	(3)
ln(pollen counts)	-0.0005	0.0000	-0.0021***
	(0.0006)	(0.0006)	(0.0007)
Rainfall (base: no rainfall)			
<1 mm	-0.0061***	-0.0059***	-0.0047**
	(0.0013)	(0.0011)	(0.0019)
1 mm≤ & < 2 mm	-0.0167***	-0.0144***	-0.0208***
	(0.0035)	(0.0024)	(0.0080)
≥ 2 mm	-0.0167***	-0.0150***	-0.0249***
	(0.0045)	(0.0041)	(0.0082)
R-squared	0.98	0.99	0.99
N	478,853	343,454	135,399
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-by-year FE	X	X	X
Prefecture-by-month FE	X	X	X

Notes: The sample is derived from cellphone mobility records from February to May for the period 2014 to 2019, with observations at the unit per day level. See Appendix G for the data construction. A total of 705 emergency response units are available. Estimates from equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. The dependent variable is the logged daily outdoor population at 2 p.m. In addition to the FEs and weather covariates in the table, we include mean wind speed, darkness, and logged population. Estimates are weighted by the population in each unit. See Appendix Table G3 for estimates of all other weather covariates. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 6—The impact of climate change under the "business as usual" scenario

		A. Maximum temperature (+4.1 ℃)				B. Number of days above 30 ℃ (+48.6 days)			
	Severity level	*Death/fatal*	*Severe*	*Moderate*	*Minor*	*Death/fatal*	*Severe*	*Moderate*	*Minor*
(1)	Increase in accidents per year	30.1	216.3	540.5	1,036.5	44.1	316.8	791.6	1,518.1
(2)	Social cost per case (in $)	*3,196,383*	*365,453*	*38,177*	*38,177*	*3,196,383*	*365,453*	*38,177*	*38,177*
(3)	Social cost per year (in million $)	96.34	79.06	20.63	39.57	141.11	115.79	30.22	57.95
(4)	Total social cost per year (in million $)	235.6				345.1			

Notes: Panel A uses the relationship between pollen counts and maximum temperature (panel A of Figure 1), while panel B employs the relationship between pollen counts and the number of days with a temperature above 30°C (panel B of Figure 1). The total social cost per year in row (4) for panel A is calculated as follows: A 4.1°C increase in mean temperature from the "business as usual" scenario (RCP 8.5) results in a daily increase in pollen counts of 686.3 (calculated as 167.4×4.1), where 167.4 is derived from panel A of Figure 1. This leads to a logged increase in pollen counts of 0.529 from the mean (calculated as log(984.34 + 686.3) - log(984.34)). Row (1) is the product of each severity level estimate from Figure 8 and 0.529, then multiplied by 120 days (February to May) of the typical pollen season in Japan, and finally multiplied by 127.4, which represents the average population (in millions) in Japan during the period 2008 to 2019. The values in row (2) are sourced from Bünnings and Schiele (2021) in the United Kingdom, using an exchange rate of 1.5 $/£. Row (3) is the product of row (1) and row (2). Row (4) is the summation of row (3) across all severity levels. Similarly, for panel B, increasing the number of days with a temperature above 30°C by 48.6 days from the "business as usual" scenario (RCP 8.5) leads to a daily increase in pollen counts of 1151.8 (calculated as 23.7×48.6), where 23.7 comes from panel B of Figure 1. This results in a logged increase in pollen counts of 0.775 (calculated as log(984.34+1151.8)- log (984.34)). The calculations for rows (1), (3), and (4) follow the same procedure.

Online Appendix
(Not for Publication)

Seasonal allergies and accidents

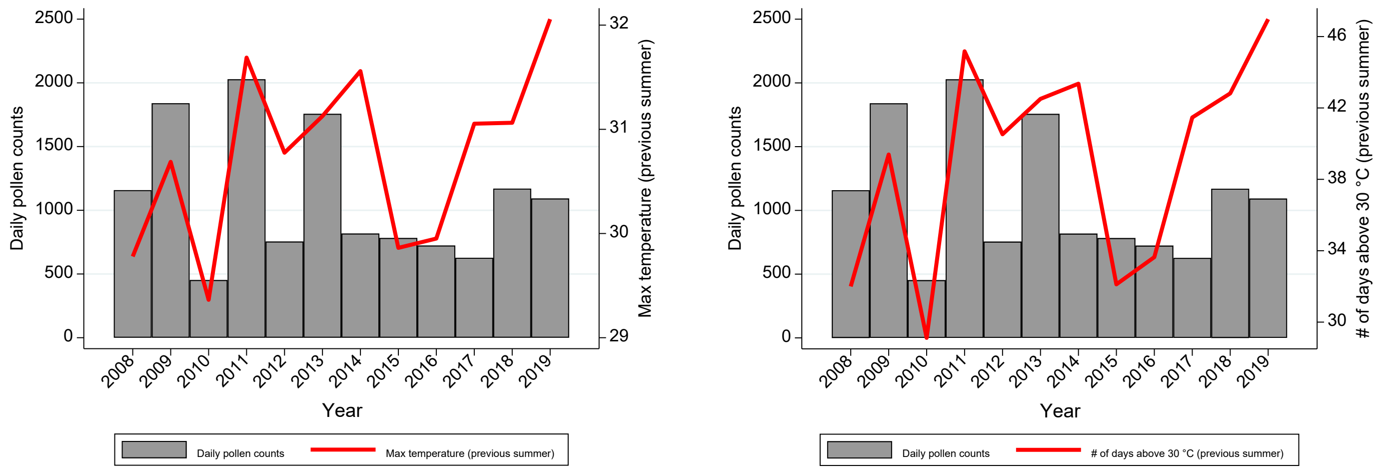
By Mika Akesaka and Hitoshi Shigeoka

Table of Contents

Appendix A: Additional figures and tables

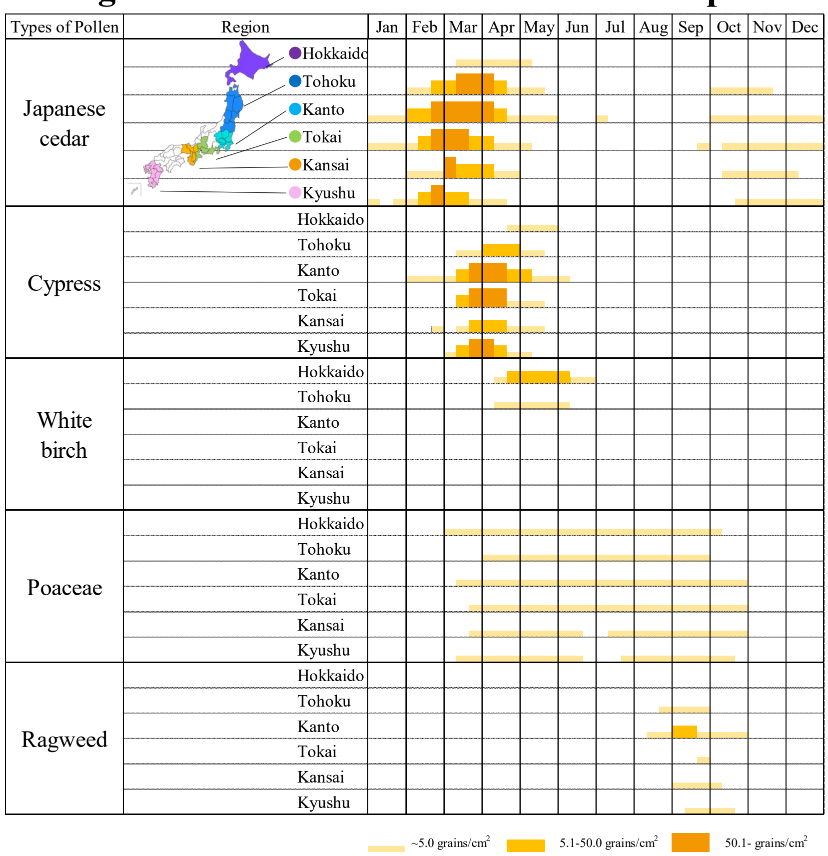
Figure A1—Time series of pollen counts and maximum temperature

A. Maximum temperature of the previous year **B. Number of days above 30℃ in the previous year**



Notes: The graphs illustrate the relationship between the average daily pollen counts (grains/m^3) from February to May and the average maximum temperature (in ℃) in panel A and the number of days the temperature exceeded 30℃ in panel B during July and August of the preceding summer. Data were collected from 120 pollen monitoring stations for the period 2008 to 2019.

Figure A2—Pollen season calendar in Japan

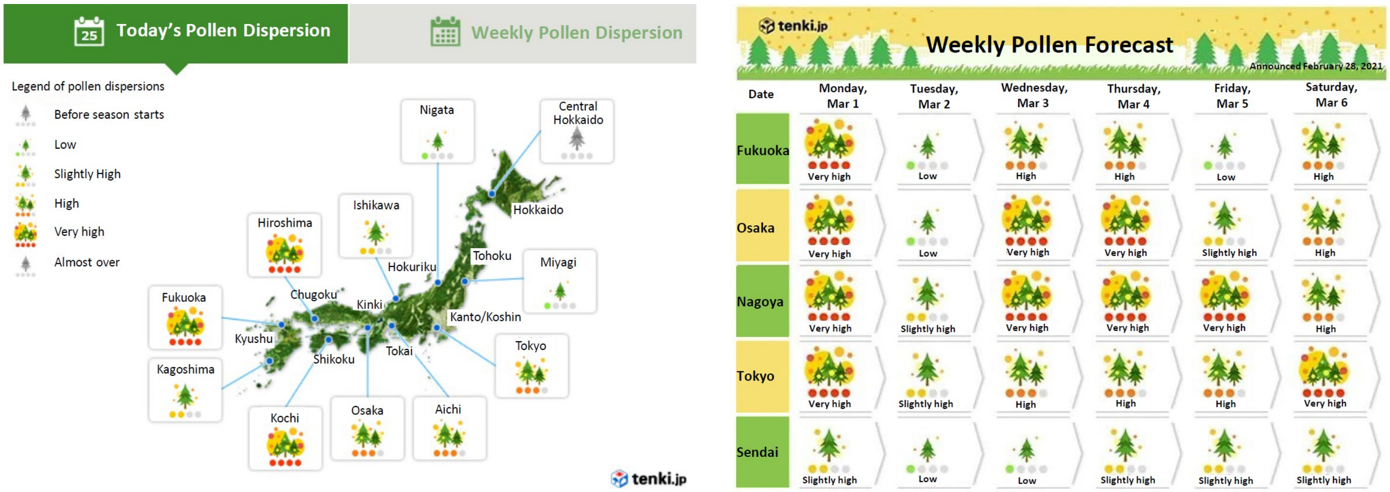


Notes: The figure displays the pollen dispersal season in Japan, for five selected pollen types: Japanese cedar, cypress, white birch, Poaceae, and ragweed—across six regions (Hokkaido, Tohoku, Kanto, Tokai, Kansai, and Kyushu). The height of the bars signifies the average pollen quantity.

Source: Kishikawa, R., E. Koto, C. Oshikawa, N. So, A. Sugiyama, A. Saito, et al. 2020. "Pollen Calendar of Important Allergenic Airborne Pollen in Japan." *Japanese Journal of Palynology*, 65(2): 55–66.

Figure A3—Pollen forecast for the current day and week

A. Current day's pollen levels B. Forecast of the week's pollen levels

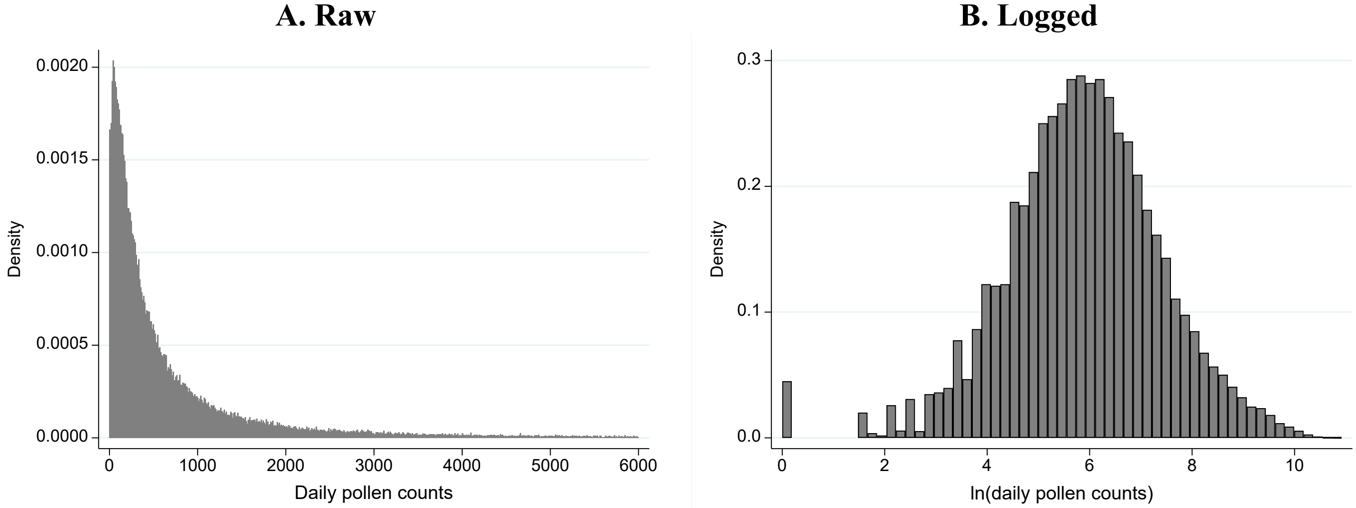


Notes: The graphs display pollen levels as reported on television and a website (https://tenki.jp/) on a typical day during Japan's pollen season. Panel A illustrates the current day's pollen levels at various locations, while panel B presents the forecasted pollen levels for the week (March 1 to March 6, as of February 28, 2021) at different locations from south to north Japan, indicating varying magnitudes. We have obtained permission to translate the original Japanese content into English.

Sources: Japan Weather Association (2022). https://tenki.jp/ (in Japanese)

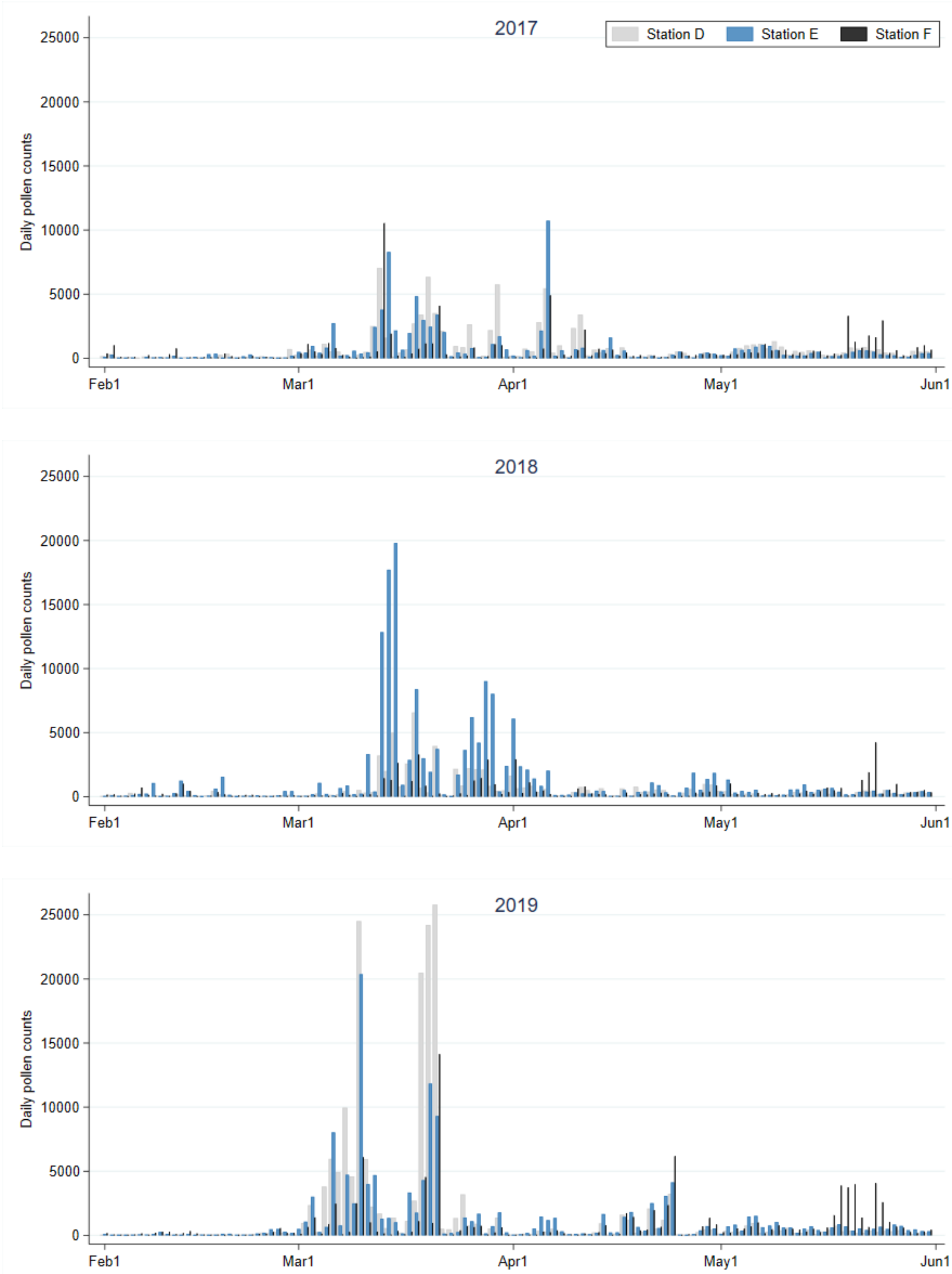
Figure A4—Distribution of the daily pollen counts

A. Raw B. Logged



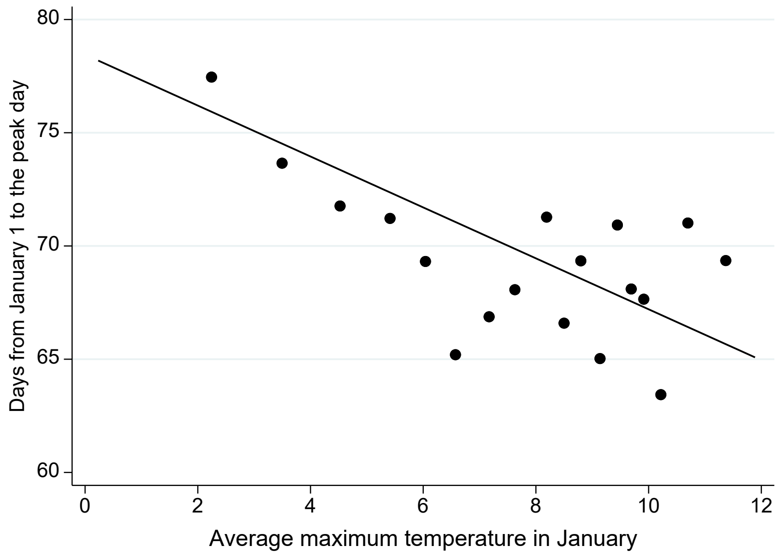
Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. Panel A displays the daily pollen counts, while panel B illustrates their logged values (grains/m^3). To accommodate zero pollen counts, we add one (0.83%) before taking the logarithm in panel B. In panel A, any daily pollen count exceeding 6,000 (3.06%) is excluded from the graph.

Figure A5—Temporal variation in pollen counts from Niigata Prefecture



Notes: The graphs display the daily variation in pollen counts (grains/m^3) for the period 2017 to 2019 at three monitoring stations in Niigata Prefecture, situated on the northern coast of Honshu, the main island of Japan.

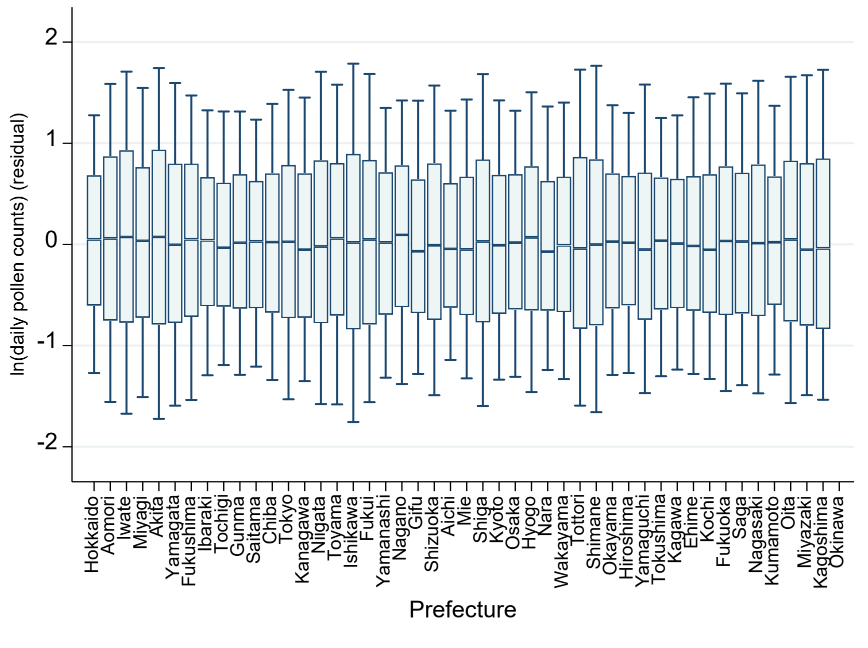
Figure A6—Winter temperature and the peak of pollen seasons



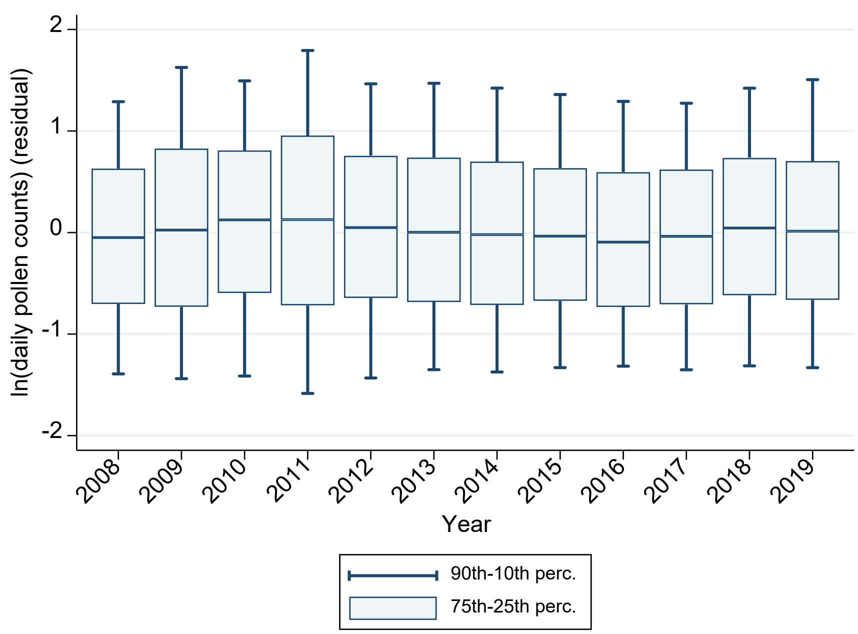
Notes: The sample encompasses all pollen monitoring stations from 2008 to 2019. The figure displays binscatter plots illustrating the relationship between the number of days from January 1st to the peak of the pollen season (on the *y*-axis) and the average maximum temperature (in ℃) in January of each year (on the *x*-axis), after controlling for the pollen monitoring station fixed effects. The peak is determined as the initial day of the year when pollen counts exceed 5,000 grains/m^3, roughly corresponding to the 96th percentile of pollen counts.

Figure A7—Identifying variation in pollen counts

A. Residual variation in logged daily pollen counts, by prefecture

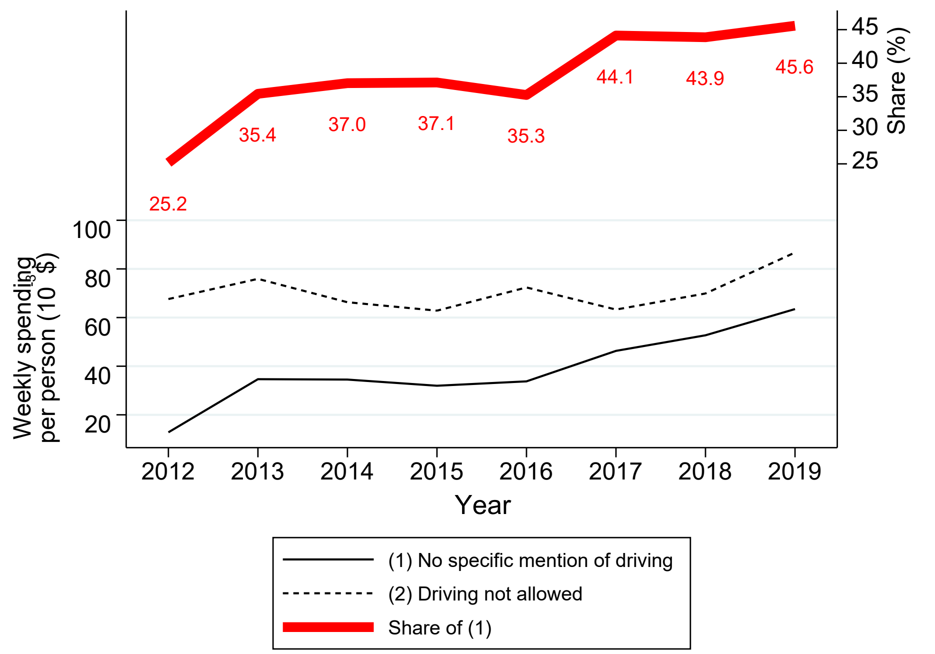


B. Residual variation in logged daily pollen counts, by year



Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. The graphs display the interquartile range and interdecile range of residual variation in logged daily pollen counts (grains/m^3) by prefecture (panel A) and by year (panel B). With a total of 46 prefectures (excluding Okinawa Prefecture, lacking a pollen monitoring station), residuals are computed after regressing logged daily pollen counts on all controls in equation (1), including unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population in each unit.

Figure A8—Time series of expenditures for seasonal allergy medications (by type)



Notes: The sample is derived from retail scanner records from February to May for the period 2012 to 2019. The figure displays the weekly expenditure (in 10^{-3} $) per individual for two categories of seasonal allergy medications: "No specific mention of driving" and "Driving not allowed," showcased on the left y-axis. Concurrently, the proportion of the former type is illustrated on the right y-axis throughout the period from 2012 to 2019. See Appendix Table A1 for the subsets corresponding to the two drug types. An exchange rate of 100 yen/$ is applied.

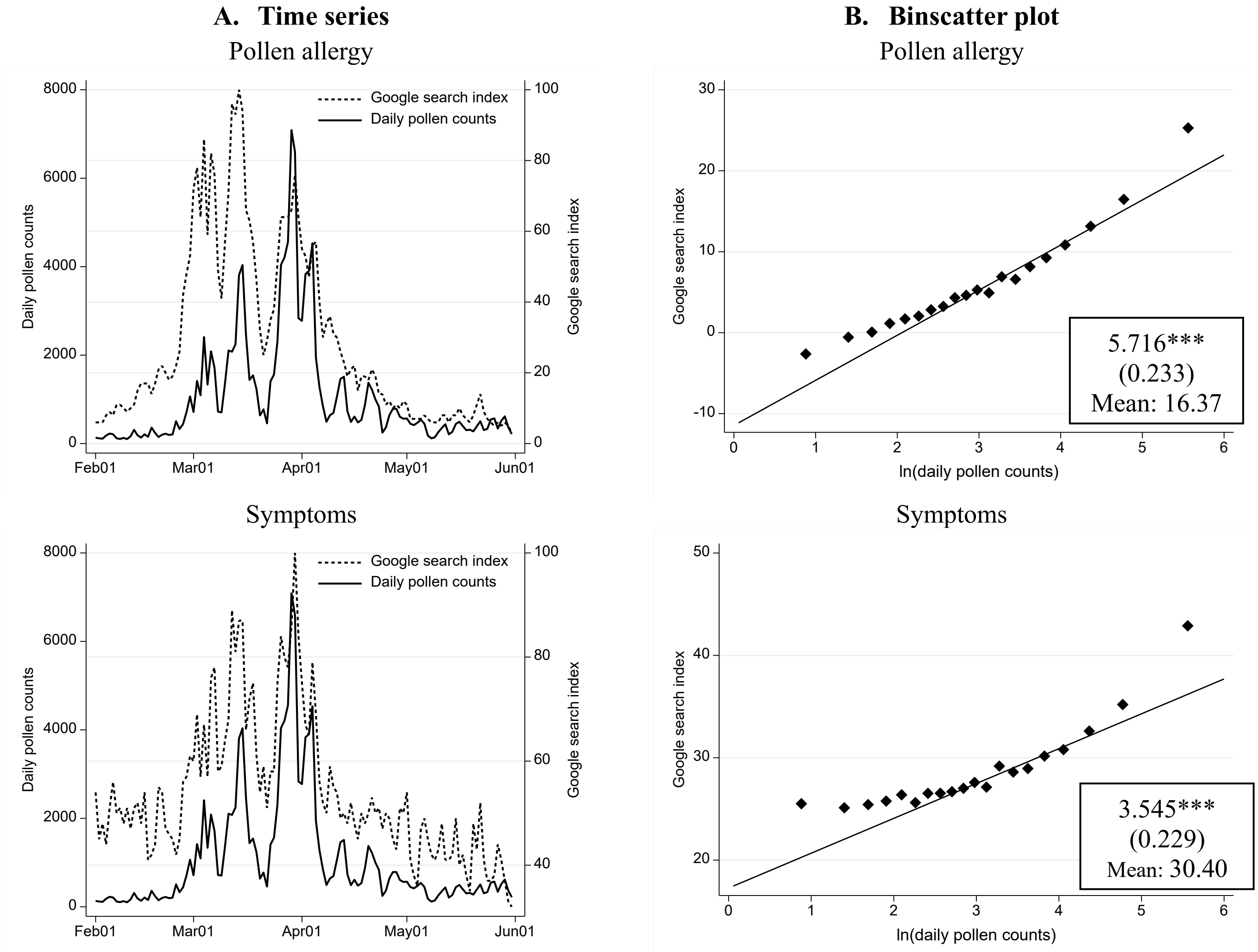
Table A1—List of medications for seasonal allergies

Brand name in Japanese	**Brand name in English**	**Year of release**	**Mention of driving**
アレジオン	Alesion	1994	Driving not allowed
エバステル	Evastel	1996	Driving not allowed
ジルテック	Zyrtec	1998	Driving not allowed
タリオン	Talion	2000	Driving not allowed
アレグラ	Allegra	2001	No specific mention of driving
アレロック	Allelock	2001	Driving not allowed
クラリチン	Claritin	2002	No specific mention of driving
ザイザル	Xyzal	2010	Driving not allowed
ディレグラ	Dellegra	2013	No specific mention of driving
ビラノア	Bilanoa	2016	No specific mention of driving
デザレックス	Desalex	2016	No specific mention of driving
ルパフィン	Rupafin	2017	Driving not allowed

Notes: The table presents brand names of allergy medications utilized for seasonal allergy treatment, indicating the year of release and any special advisories regarding driving post-medication consumption. Medications shaded in gray lack explicit instructions regarding driving. Note that our accident data primarily covers the period from 2008 to 2019.

Appendix B: Symptoms of seasonal allergies

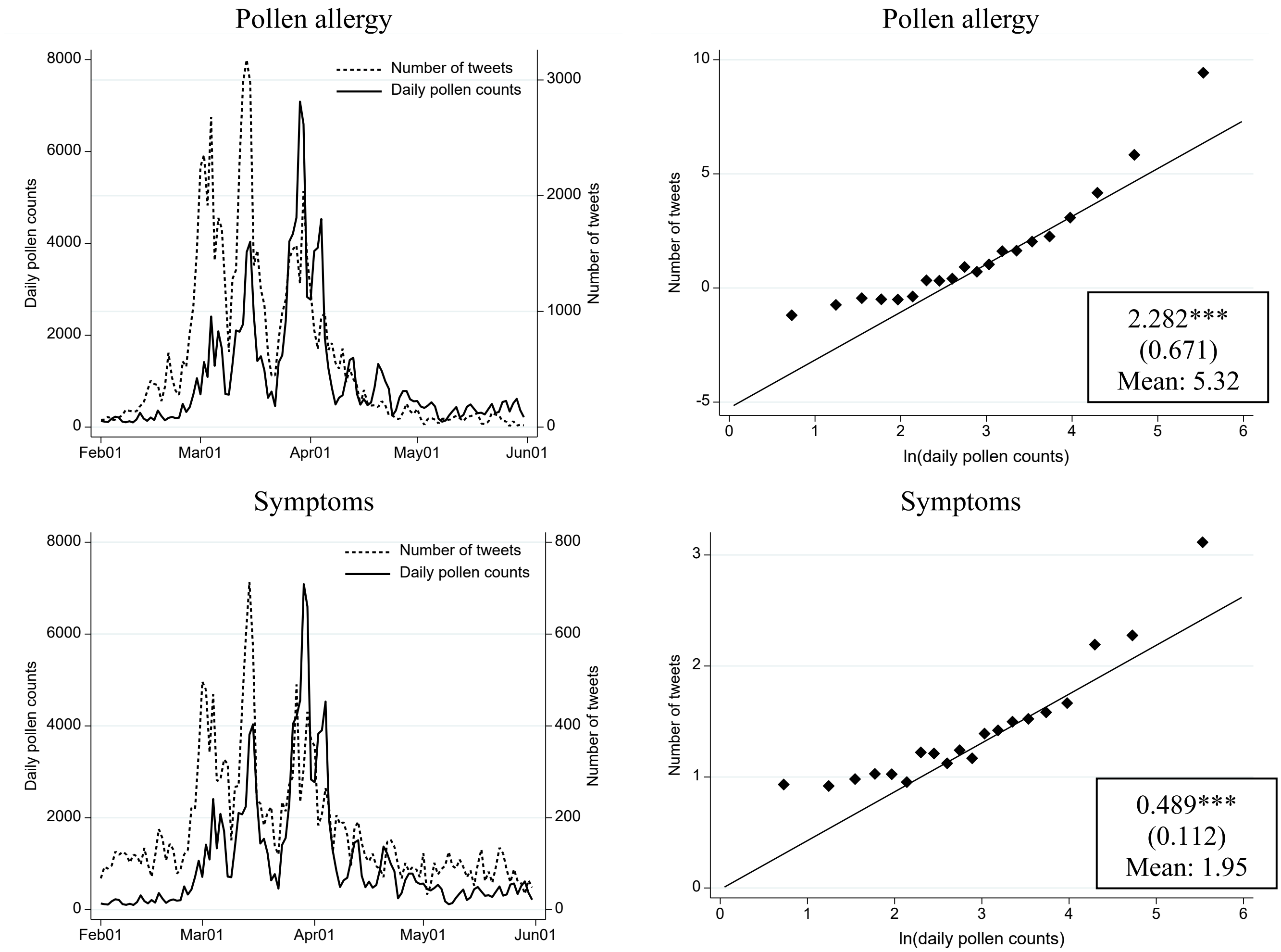
Figure B1—Daily pollen counts and Google Trends



Notes: The sample is derived from Google Trends data, with observations at the prefecture-per-day level. Panel A illustrates the time-series patterns of average daily pollen counts (grains/m^3) and Google search index for pollen allergy-related and symptom-related keywords in 2018 on a national scale. See Appendix Table B1 for the list of search terms within each category. June is omitted because only four stations in Hokkaido (the northernmost island of Japan) were still active in June. Panel B presents the binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the x-axis) and the Google search index for the same keywords (on the y-axis), after controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population for the period 2016 to 2019 (N= 21,551). Estimates from the variants of equation [1], where unit fixed effects are replaced by prefecture fixed effects, are reported in the box. Standard errors clustered at the prefecture level are reported in parentheses. Estimates are weighted by the population in each prefecture per year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Figure B2—Daily pollen counts and tweets

A. Time series **B. Binscatter plot**



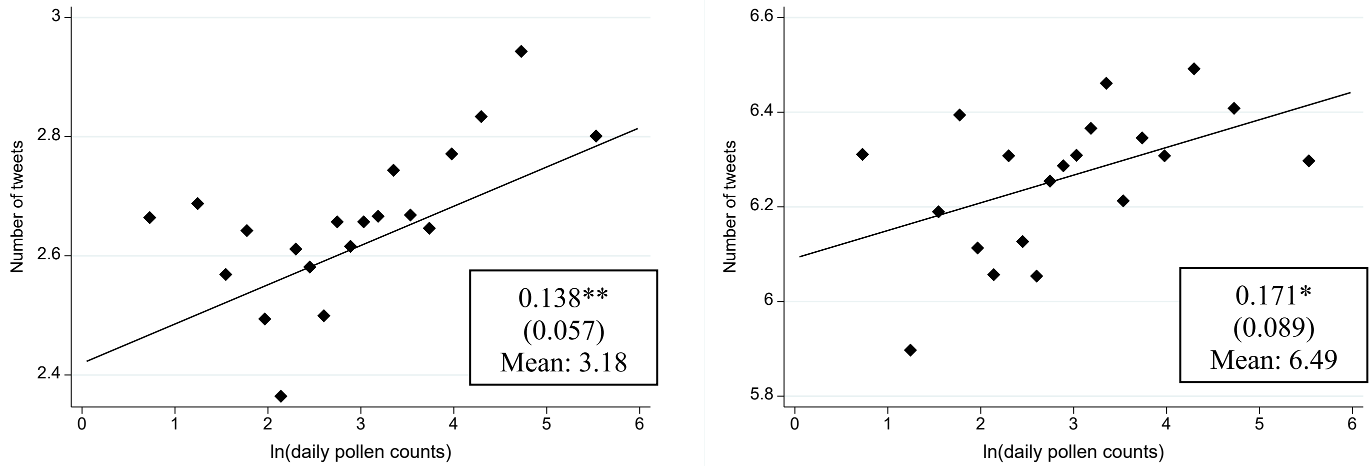
Notes: The sample is derived from Twitter data, with observations at the prefecture-per-day level. Panel A presents the time series patterns of the average daily pollen counts (grains/m^3) and the number of tweets for pollen allergy-related and symptom-related keywords in 2018 on a national scale. See Appendix Table B1 for the list of search terms within each category. June is omitted because only four stations in Hokkaido (the northernmost island of Japan) were still active in June. Panel B displays the binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the *x*-axis) and the number of tweets for the same keywords (on the *y*-axis), after controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population for the period 2016 to 2019 (N= 21,551). Estimates from the variants of equation [1], where unit fixed effects are replaced by prefecture fixed effects, are provided in the box. Standard errors clustered at the prefecture level are enclosed in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Figure B3—Binscatter plot of pollen counts and tweets: Sleep-related

Sleepiness and **Sleeplessness** panels:

Sleeplessness
("Having a hard time falling asleep")

Sleepiness
("Feeling sleepy")



Notes: The sample is derived from Twitter data for the period 2016 to 2019, with observations at the prefecture per day level (N=21,551). The graphs display binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the x-axis) and the frequency of tweets containing the terms "Hard time falling asleep" and "Feeling sleepy" (on the y-axis), after controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. See Appendix Table B1 for the categorized list of search terms. Estimates from the variants of equation [1], where unit fixed effects are replaced by prefecture fixed effects, are provided in the box. Standard errors clustered at the prefecture level are enclosed in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

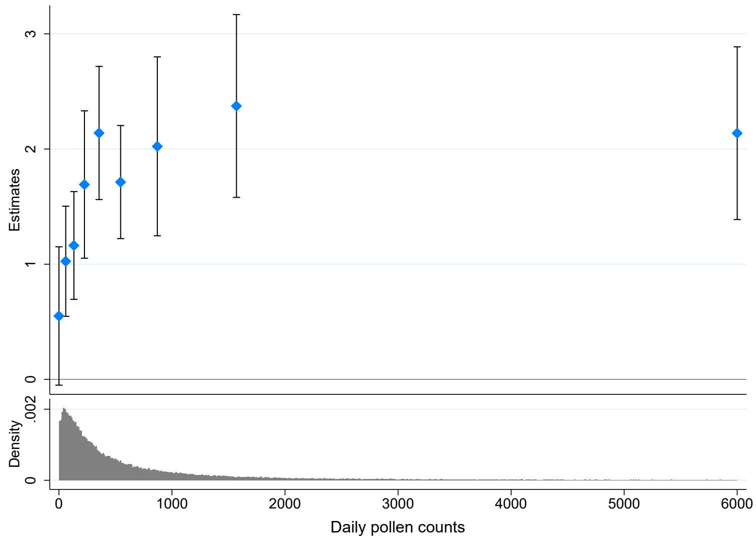
Table B1—List of search terms for symptoms

Category #	Categories	Japanese	English
Common for Google Trends and Tweets			
1	**Pollen allergy**	花粉	Pollen
		花粉症	Pollen allergy
		スギ花粉	Japanese cedar pollen
2	**Symptoms**	鼻水	Runny nose
		鼻づまり	Nasal congestion
		くしゃみ	Sneezing
		目のかゆみ	Itchy eyes
Only for Tweets (sleep-related)			
3	**Sleeplessness**	寝付けない，ねつけない	Having a hard time falling asleep
		寝れない，ねれない	
		眠れない，ねむれない	
4	**Sleepiness**	眠い，ねむい	Feeling sleepy
		眠たい，ねむたい	
		眠すぎる，ねむすぎる	

Notes: The table lists the keywords for each category in both Japanese and English (for reference).

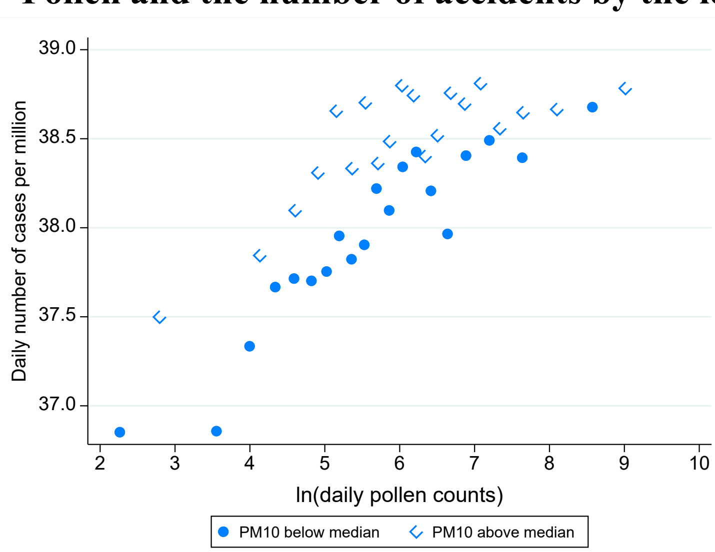
Appendix C: Ambulance records

Figure C1—Dose responses



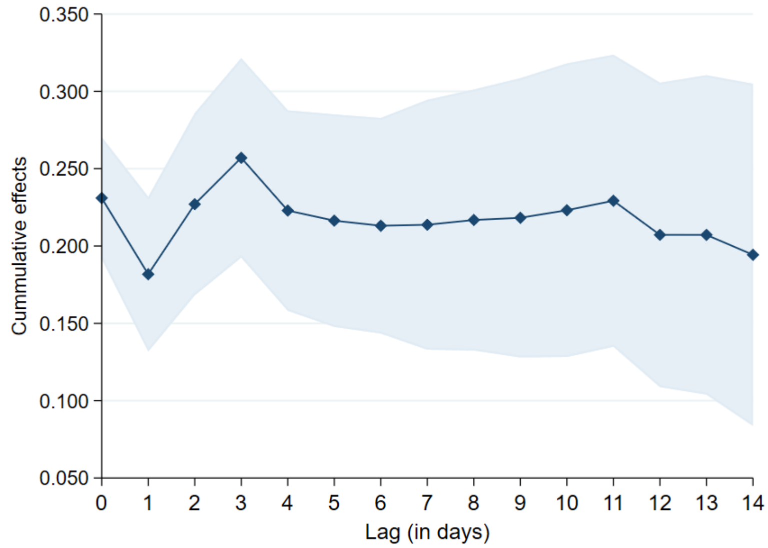
Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N= 970,309). A total of 705 emergency response units are available. The plots exhibit estimates and 95% confidence intervals of the treatment effects of daily pollen counts (in levels), using a variant of equation [1] where the logged daily pollen is replaced by dummies for each decile of daily pollen levels (grains/m^3). The dependent variable is the number of daily cases per million people. Standard errors are clustered at the pollen monitoring station levels. All specifications include unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population of each unit. The histogram at the bottom displays the distribution of daily pollen counts (grains/m^3).

Figure C2—Pollen and the number of accidents by the level of PM_{10}



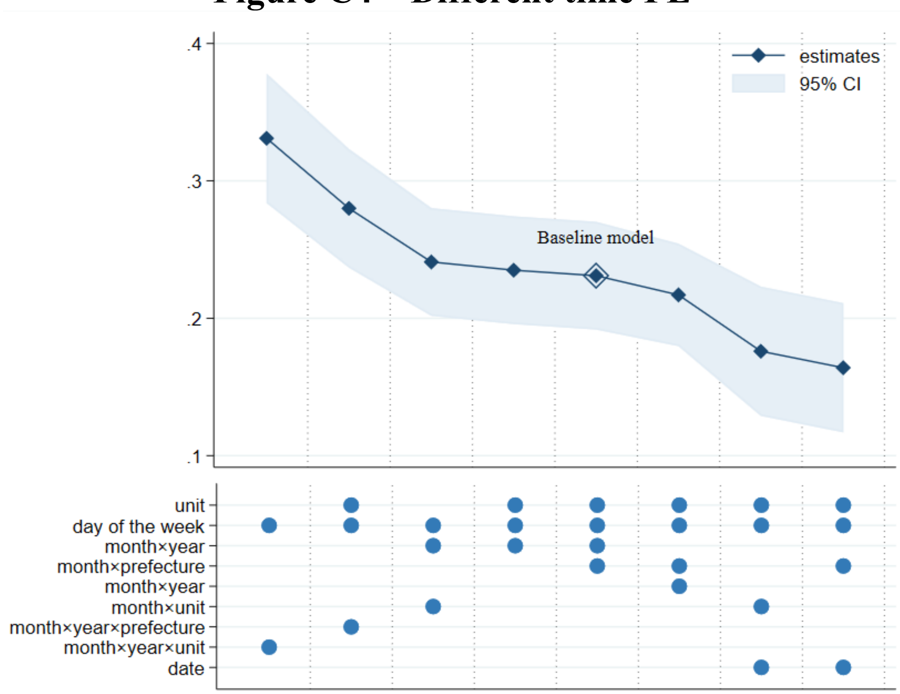
Notes: The sample is derived from ambulance records for the period 2009 to 2019, with observations at the unit per day level (N= 806,839). A total of 705 emergency response units are available. The figure displays binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the *x*-axis) and the number of daily cases per million people for all accidents (on the *y*-axis), categorized as below and above the daily median of PM_{10}, after controlling for unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population of each unit.

Figure C3—Varying window for the sum of coefficients in the distributed lag model



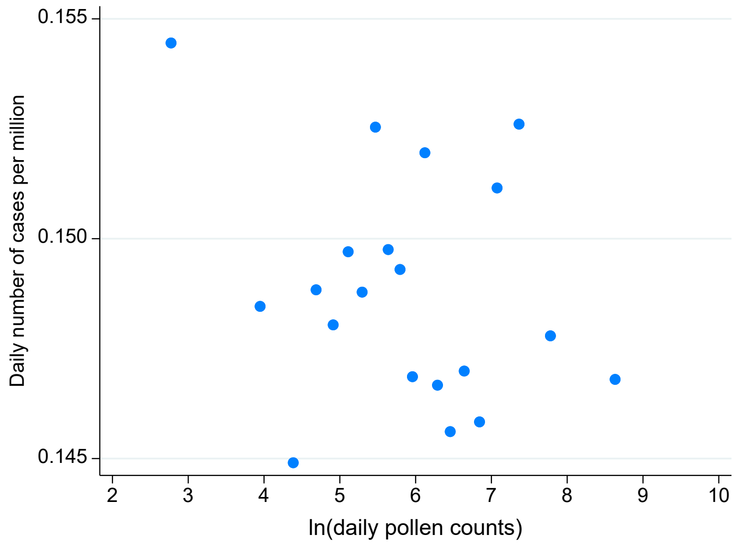
Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N= 970,309). A total of 705 emergency response units are available. The plots depict the estimates and 95% confidence intervals of the sum of coefficients (= $\sum_{k\in K}\beta_k$) in the distributed lag model derived from equation [2], with varying windows of up to 14 days. The dependent variable is the daily number of cases per million people. All specifications include fixed effects for unit, month-by-year, month-by-prefecture, and day-of-week. Additionally, logged pollen counts and weather covariates (precipitation, temperature, wind speed) for the days preceding and following the observation date within the specified time horizon are included. Estimates are weighted by the population of each unit.

Figure C4—Different time FE



Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N= 970,309). A total of 705 emergency response units are available. The plots display estimates and 95% confidence intervals of treatment effects on logged daily pollen counts from equation [1] under various specifications with high-dimensional unit and time fixed effects. Standard errors are clustered at the pollen monitoring station level. The dependent variables are the number of daily cases per million people. The baseline model includes fixed effects for unit, month-by-year, month-by-prefecture, and day-of-week. All specifications additionally include weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population of each unit.

Figure C5—Pollen counts and emergency ambulance transports due to cancer



Notes: The sample is derived from ambulance records for the period 2015 to 2019, with observations at the unit per day level (N= 407,463). A total of 705 emergency response units are available. These ambulance records encompass detailed diagnosis information, equivalent to ICD10, starting from 2015. The figure displays binscatter plots illustrating the relationship between the logged daily pollen counts (grains/m^3, on the *x*-axis) and the frequency of daily emergency ambulance transports due to cancer per million people (on the *y*-axis), after controlling for unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population of each unit.

Table C1—Pollen and pollution interactions

	(1)	(2)
ln(pollen counts)	0.230***	0.267***
	(0.021)	(0.027)
1($PM_{10} \geq$ median)		0.068
		(0.222)
ln(pollen) × 1($PM_{10} \geq$ median)		-0.053
		(0.036)
R-squared	0.46	0.46
N	806,839	806,839
Unit FE	X	X
Day-of-week FE	X	X
Month-by-year FE	X	X
Prefecture-by-month FE	X	X

Notes: The sample is derived from ambulance records for the period 2009 to 2019, with observations at the unit per day level (N= 806,839). Pollution data are available starting from 2009. A total of 705 emergency response units are available. The dependent variable is the daily number of cases per million people for all accidents. Column (1) replicates the baseline estimates presented in Table 2 for the subset with available pollution data. Column (2) presents estimates derived from the variation of equation [1], where a dummy variable, which takes a value of 1 when the daily PM_{10} level exceeds the median, and 0 otherwise, and its interaction with logged pollen counts is also included. Standard errors clustered at the pollen monitoring station level are reported in parentheses. In addition to the fixed effects listed in the table, weather covariates (precipitation, temperature, wind speed), darkness, and logged population are included in the estimation. Estimates are weighted by the population of each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table C2—Different levels of clustering

Clustering variables	N of clusters	SE	
		0.231	
Monitoring stations (baseline)	120	(0.020)	***
Monitoring stations and date	120 + 1,796	(0.028)	***
Monitoring stations and month-year	120 + 60	(0.030)	***
Unit	705	(0.019)	***
Unit and date	705 + 1,796	(0.028)	***
Unit and month-year	705 + 60	(0.031)	***
Prefecture	47	(0.016)	***
Prefecture and date	47 + 1,796	(0.025)	***
Prefecture and month-year	47 + 60	(0.028)	***
Conley (50 km)	-	(0.018)	***
Conley (100 km)	-	(0.019)	***
Conley (150 km)	-	(0.020)	***

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N= 970,309). A total of 705 emergency response units are available. The dependent variable is the number of daily cases per million people. Estimates from equation [1] are reported. All specifications include unit, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. The numbers of pollen monitoring stations, units, and prefectures are 120, 705, and 46, respectively. The last three rows present spatially clustered standard errors following the methodology outlined in Conley (1999), employing distance cutoffs of 50, 100, and 150 km, respectively. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table C3—Alternative specifications

	(1) level-log OLS (Baseline)	(2) log-log OLS	(3) Poisson pseudo-maximum likelihood (PPML)
ln(pollen counts)	0.231***	0.0054***	0.030***
	(0.020)	(0.0006)	(0.003)
R-squared	0.46	0.90	-
N	970,309	970,309	970,309
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-by-year FE	X	X	X
Prefecture-by-month FE	X	X	X

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level (N=970,309). A total of 705 emergency response units are available. Column (1) reports the results from Table 2 (baseline) for ease of comparison. Column (2) reports estimates from the variant of equation [1], wherein the dependent variable takes the logarithm of the number of daily cases per million people. Estimates are weighted by the population in each unit in columns (1) and (2). Column (3) reports the marginal effect of Poisson pseudo-maximum likelihood (PPML) using the *dydx* command in Stata. The estimate in column (3) can be converted to 0.222 cases per million people (= 0.030/0.135), where 0.135 is the average population in a million, which is comparable to the baseline estimate in column (1). The standard errors clustered at the pollen station level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table C4—Placebos

	(1)	(2)	(3)
	Baseline	Assigning last year's pollen counts	Assigning next year's pollen counts
ln(pollen counts)	0.231***	0.008	0.021
	(0.020)	(0.022)	(0.022)
R-squared	0.46	0.47	0.46
N	970,309	879,777	881,226
Mean of dep. var	33.03	33.21	32.89
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-by-year FE	X	X	X
Prefecture-by-month FE	X	X	X

Notes: The sample is derived from ambulance records for the period 2008 to 2019, with observations at the unit per day level. A total of 705 emergency response units are available. The dependent variable is the number of daily cases per million people. The estimates from equation [1] are reported. All specifications include fixed effects for unit, month-by-year, month-by-prefecture, and day-of-week, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Column (1) replicates the estimates from Table 2 (baseline) for ease of comparison. Columns (2) and (3) falsely assign the pollen levels of the corresponding day from the previous and subsequent years, respectively (for instance, for March 3, 2018, in unit X, columns (2) and (3) assign the pollen levels of March 3, 2017, and March 3, 2019, within the same unit X). Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Appendix D: Police records

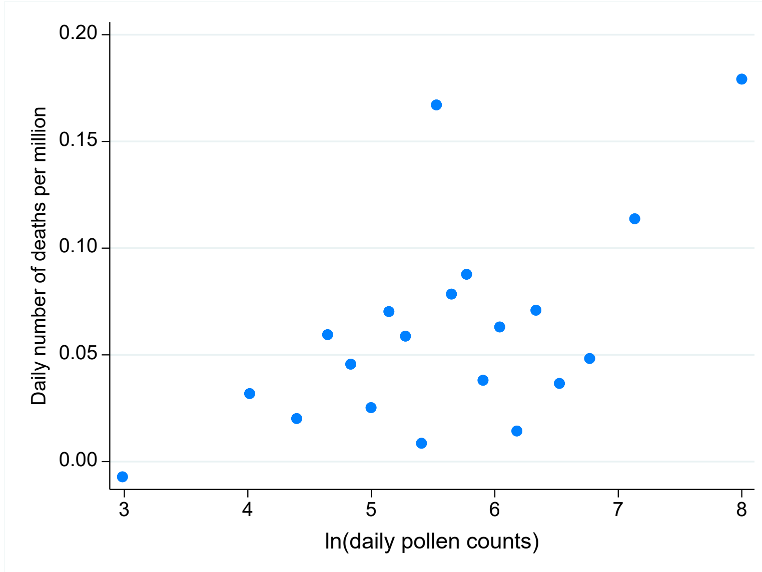
The police records encompass all 690,415 traffic accidents (or 106,533 during the pollen season) occurring between 2019 and 2020. These data are compiled at the individual accident level, detailing information such as location, date, and time of occurrence. Unlike the ambulance service, which operates at a unit level (N=705), the police service is administered at the municipal level (N=1,700). Consequently, we aggregate casualty figures to the municipal-day level by consolidating hourly observations within municipalities.

Figure D1 illustrates the binscatter plots depicting the relationship between the logged average daily pollen count (grains/m^3) and the number of traffic fatalities per million people, while controlling for municipality, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. The figure clearly demonstrates the positive relationship between these variables.

Table D1 presents the estimates from equation [1], wherein the unit fixed effect is replaced by the municipality fixed effect. For ease of comparison, column (1) shows the death/fatal estimates for traffic accidents recorded between 2008 and 2019, sourced from ambulance records. Column (2) displays the mortality estimates derived from the 2019 to 2020 police records. The estimate of 0.0040 (p-value < 0.01) in column (2) surpasses the 0.0026 estimate from column (1), suggesting a potential underestimation of the impact of pollen exposure on traffic accident fatalities.[1] However, at conventional levels, the two estimates are not statistically distinguishable.

[1] One plausible explanation for this observation is that police records encompass all deaths resulting from traffic accidents within 24 hours, unlike ambulance records, which solely encompass deaths occurring upon hospital admission. Notably, the count of traffic accidents resulting in death recorded in our ambulance records for 2019 is 1,771, whereas the corresponding figure reported to the National Police Agency (NPA) is 3,215 (NPA 2022).

Figure D1—Pollen and mortality due to traffic accidents (police records)



Notes: The sample is derived from police records for the period 2019 to 2020, with observations at the municipality per day level (N= 399,749). A total of 1,700 municipalities exist. The figure displays binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the *x*-axis) and the number of deaths per million people within 24 hours resulting from traffic accidents (on the *y*-axis), after controlling for municipality, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population.

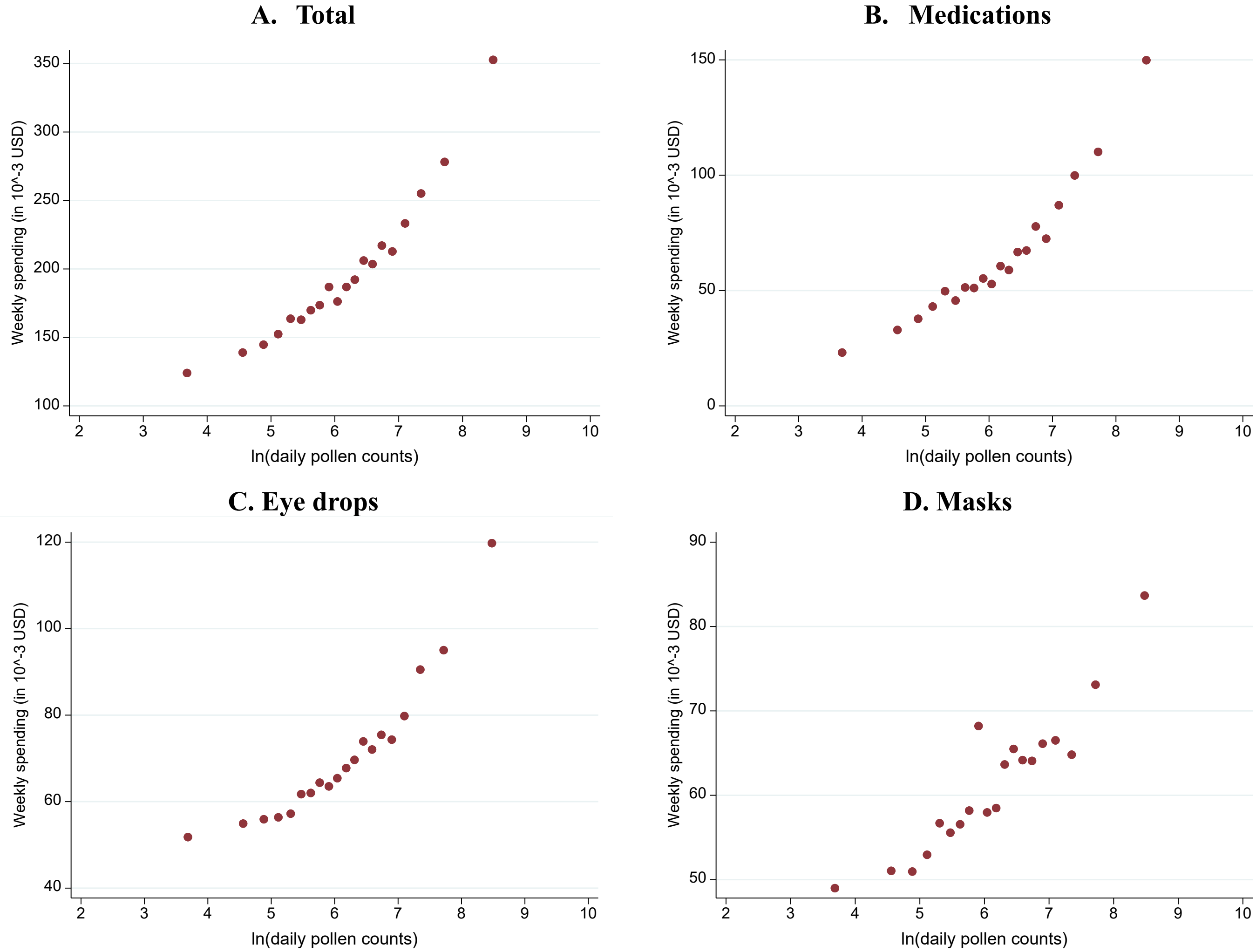
Table D1—Mortality due to traffic accidents (ambulance records vs. police records)

	Ambulance records	Police records
	(1)	(2)
ln(pollen counts)	0.0026***	0.0040***
	(0.0007)	(0.0015)
R-squared	0.01	0.01
N	970,309	399,749
N of unit/municipality	705	1,700
N of clusters	120	120
Mean of dep. var	0.077	0.125
Unit/municipality FE	X	X
Day-of-week FE	X	X
Month-by-year FE	X	X
Prefecture-by-month FE	X	X

Notes: The sample for column (1) is derived from ambulance records for the period 2008 to 2019, while the sample for column (2) is derived from police records for the period 2019 to 2020. The level of observation is units per day for column (1) and municipality per day for column (2). There are a total of 705 emergency response units and 1,700 municipalities. The dependent variable is the number of deaths due to traffic accidents per million people. Estimates from equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. In addition to the fixed effects listed in the table, we include weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population in each unit in column (1) and by the population in each municipality in column (2). Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Appendix E: Avoidance behavior from retail scanner data

Figure E1—Pollen count and weekly expenditure on allergy products



Notes: The sample is derived from retail scanner data from February to May for the period 2012 to 2019, with observations at a weekly per-person level (N= 4,303,417). The graphs display binscatter plots illustrating the relationship between logged daily mean pollen counts (grains/m^3, on the *x*-axis) and weekly expenditure per person (in 10^{-3}\$, on the *y*-axis) for all allergy products in panel A, and individually for each product in panels B to D: medications (panel B), eye drops (panel C), and masks (panel D), after controlling for municipality, month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. The shares of medications (panel B), eye drops (panel C), and masks (panel D) are 35%, 37%, and 28%, respectively. An exchange rate of 100 yen/$ is applied.

Table E1—Nielsen Panel Data vs. Quick Purchase Report

Feature	Nielsen Homescan Panel (U.S.)	Quick Purchase Report (QPR) by Macromill
Country	United States	Japan
Unit of Observation	Household	Household
Method	Homescan + manual report (partly)	Homescan
Target Product	UPC-coded packaged goods + some non-barcode items (manual report)	JAN-coded packaged goods
Coverage Period	2004-	2011-
Sample Size	40,000–60,000	Approximately 35,000
Panel Structure	Yes	Yes
Nationally Representative	Yes	Yes
Information Included:		
Purchase Date	Yes	Yes
Retailer/Channel Type	Yes	Yes
Online Purchase	Yes	Yes
Price Paid	Yes	Yes
Coupon/Deal Flag	Yes	No

Sources:
Nielsen: https://www.chicagobooth.edu/research/kilts/research-data/nielseniq?utm_source=chatgpt.com
Macromill: https://www.e-stat.go.jp/bigdataportal/dataintro/253

Table E2—Summary statistics of retail scanner data

Variables	Obs	Mean	Std. dev.	Min	Max
A. Outcomes (weekly per person in $\$10^{-3}$)					
Spending: Total	4,303,417	295.78	2343.95	0	2,141,620
Spending: Medications	4,303,417	109.94	1528.34	0	227,200
Spending: Eye drops	4,303,417	103.41	1018.20	0	104,000
Spending: Masks	4,303,417	82.52	1324.56	0	2,141,620
B. Individual characteristics					
Ages: 0–24	4,303,417	0.13	0.33	0	1
Ages: 25–44	4,303,417	0.38	0.48	0	1
Ages: 45–64	4,303,417	0.38	0.49	0	1
Ages: 65 years and older	4,303,417	0.11	0.32	0	1
Female	4,303,417	0.50	0.50	0	1
Student	4,303,417	0.11	0.31	0	1
Household head	4,303,417	0.46	0.50	0	1
Have kids	4,303,417	0.55	0.50	0	1
Own house	4,303,417	0.58	0.49	0	1
Annual salary category	4,303,417	2.61	2.22	1	13
C. Regressors (daily average in a week)					
Pollen counts (grains/m^3)	4,303,417	843.2	1337.4	0	22,812
Logged (Pollen counts)	4,303,417	0.1	0.2	0	3.9
Precipitation (mm)	4,303,417	12.0	6.0	-8	26
Average temperature (℃)	4,303,417	2.8	0.9	0	11.6
Average wind speed (m/s)	4,303,417	10.5	1.3	7	13

Notes: The sample is derived from retail scanner data from February to May for the period 2012 to 2019, with observations at a weekly per-person level. Expenditure is measured in units of 10^{-3} \$. An exchange rate of 100 yen/\$ is applied.

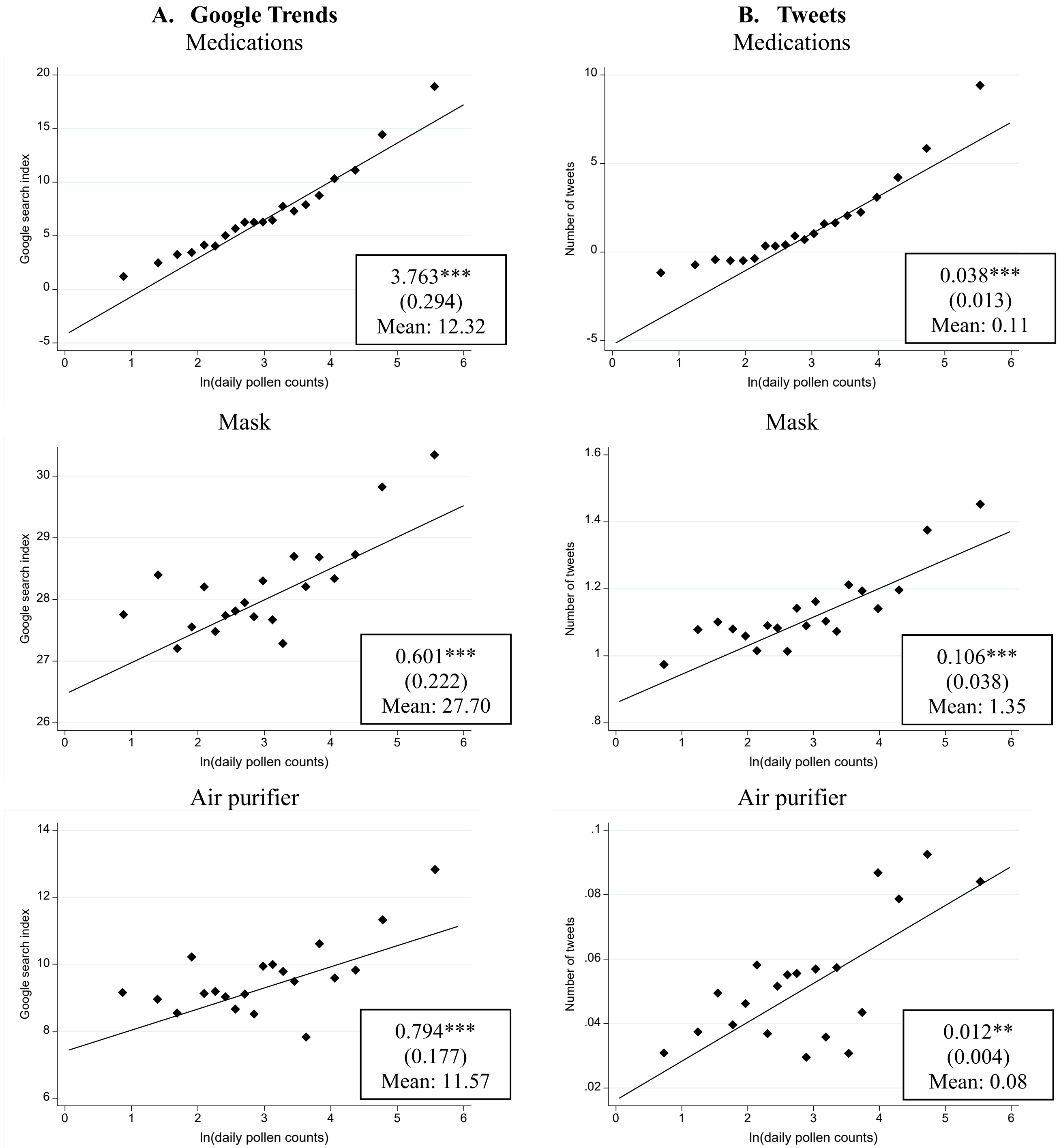
Table E3—Purchasing allergy products: Heterogeneity

	A. By age groups		B. By gender	
	Non-elderly	Elderly	Male	Female
	(1)	(2)	(3)	(4)
ln(pollen counts)	46.686***	43.916***	38.994***	49.415***
	(3.122)	(3.417)	(2.325)	(3.604)
R-squared	0.008	0.005	0.008	0.007
N	3,147,182	934,660	2,137,760	2,165,657
Mean of dep. var (in 10^{-3} \$)	306.88	316.50	248.98	341.97
Municipality FE	X	X	X	X
Year-prefecture FE	X	X	X	X
Week FE	X	X	X	X

Notes: The sample is derived from retail scanner data from February to May for the period 2012 to 2019, with observations at a weekly per-person level. The dependent variable is the weekly expenditure (in 10^{-3} \$) on all allergy products, using an exchange rate of 100 yen/\$. Estimates from the variant of equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. In addition to the fixed effects listed in the table, weather covariates (precipitation, temperature, wind speed), and darkness are included. The elderly category comprises individuals aged 60 years and older, while the non-elderly category encompasses everyone else. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Appendix F: Avoidance behavior from Google Trends/Tweets

Figure F1—Pollen and Google Trends/Tweets



Notes: The samples are derived from Google Trends data for panel A and Twitter data for panel B for the period 2016 to 2019. The level of observation is at the prefecture level per day. The graphs display binscatter plots illustrating the relationship between logged daily pollen counts (grains/m^3, on the *x*-axis) and the Google search index in panel A, and the number of tweets in panel B for keywords related to medications (on the *y*-axis), masks, and air purifiers, after controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. See Appendix Table F1 for the list of search terms within each category. Estimates from the variant of equation [1], wherein unit fixed effects are replaced by prefecture fixed effects, are presented in the box. Standard errors, clustered at the prefecture level, are reported in parentheses. Estimates are weighted by the population in each prefecture per year. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table F1—List of search keywords

Category #	Categories	Japanese	English
1	**Medications** (product name of popular allergy medications)	アレジオン	Alesion
		アレグラ	Allegra
		クラリチン	Claritin
2	**Mask**	マスク	Mask
3	**Air purifier**	空気清浄機	Air purifier

Notes: The table lists the keywords for each category in both Japanese and English (for reference).

Appendix G: Avoidance Behavior from Cellphone Mobility Records

Our geolocation data, referred to as "Mobile Spatial Statistics" (MSS), is provided by NTT DOCOMO, Inc., Japan's largest mobile phone carrier. MSS utilizes the location information of 85 million NTT DOCOMO users (as of March 2022) to provide population estimates at a 500×500 meter mesh on an hourly basis across Japan. For detailed procedures on constructing these population estimates, see Terada et al. (2013).

Our dataset on mobility measures is structured as follows: Firstly, for each municipality, we select a 500×500 meter mesh with the highest number of establishments in the customer service industry (e.g., accommodations, restaurants, and entertainment) based on information from the 2016 Economic Census (MIC 2019).[2] This choice of the service industry aims to capture bustling areas such as business districts, shopping, and dining areas, which are more likely to represent the population engaged in outdoor activities. Secondly, we provide the list of these meshes to NTT DOCOMO, Inc., which returns the estimated population at each mesh for the period from February 2014 to May 2019. Thirdly, we aggregate the estimated population at the unit level by calculating the average across all municipalities within the unit. We specifically use the estimated population at 2 p.m. as the daily population in commercial areas tends to peak around this time (Seike et al. 2015). This measure serves as a proxy for engaging in outdoor activities, hereafter referred to as the "outdoor population," which we analyze to examine avoidance behavior.

Finally, we briefly discuss the advantages and disadvantages of this dataset. There are two types of geolocation data in Japan: the first originates from the leading smartphone mapping application in Japan, "Docomo Chizu NAVI," which collects GPS coordinates of each smartphone device whenever the device is turned on. A notable feature of this application is its ability to effectively track individuals over time (albeit only for recent years). Researchers can identify individuals' "home" locations as the most frequent locations of geographically contiguous stays (Miyauchi et al. 2021) and measure whether individuals leave their homes. However, the drawback is that the sample is limited to individuals who have granted permission to share their location information, leading to selection biases in both application users and those who consent, resulting in a relatively small sample size (545,000 users as of 2019). The second type of data, including ours, is based on the transmission of information from each mobile terminal (in our case, 85 million users) to base stations when mobile devices are turned on. This type of data offers a more nationally representative sample with broad spatial coverage of the entire country, albeit providing only hourly estimated population data for each area.

Given that the primary objective of this study is to provide nationally representative estimates of the effects of pollen exposure on accidents and corresponding avoidance behaviors over an extended period, we have chosen to analyze the latter dataset. Due to its representativeness and the extensive time span covered by the sample, this dataset has been widely utilized, particularly for measuring people's mobility during the COVID-19 pandemic (e.g., Kondo 2021; Kuroda et al. 2022).

[2] Due to budgetary constraints, our dataset comprises one mesh per municipality. Nevertheless, we affirm that our mobility measure effectively encompasses overall daytime outdoor activity, utilizing the 2019 data, wherein we possess outdoor population statistics for all meshes. Notably, our mobility measure derived from the representative mesh exhibits a correlation as high as 0.889 with the summary measure, which aggregates data from all meshes hosting at least one service establishment.

References

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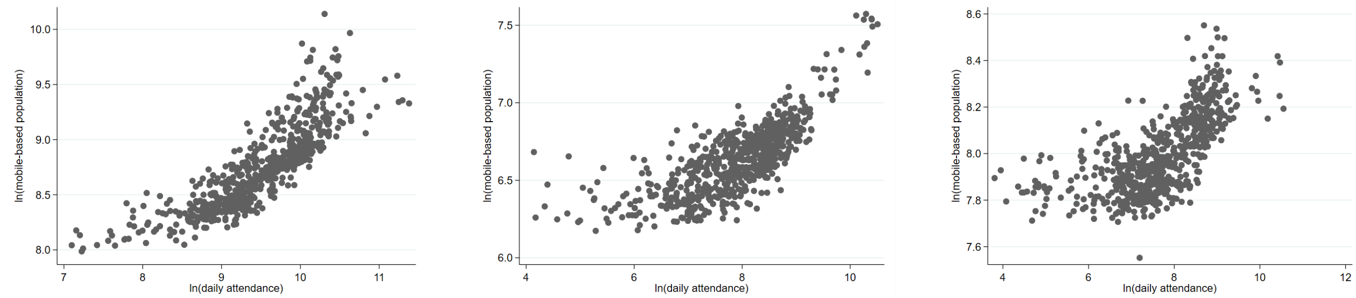
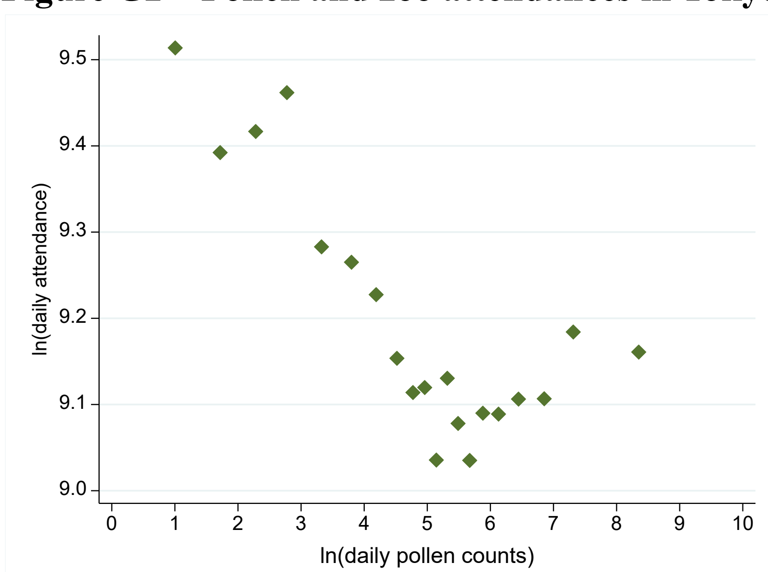
Figure G1—Actual Zoo attendance and population estimate from cellphone mobility records

A. Ueno Zoo B. Tama Zoological Park C. Inokashira Park Zoo



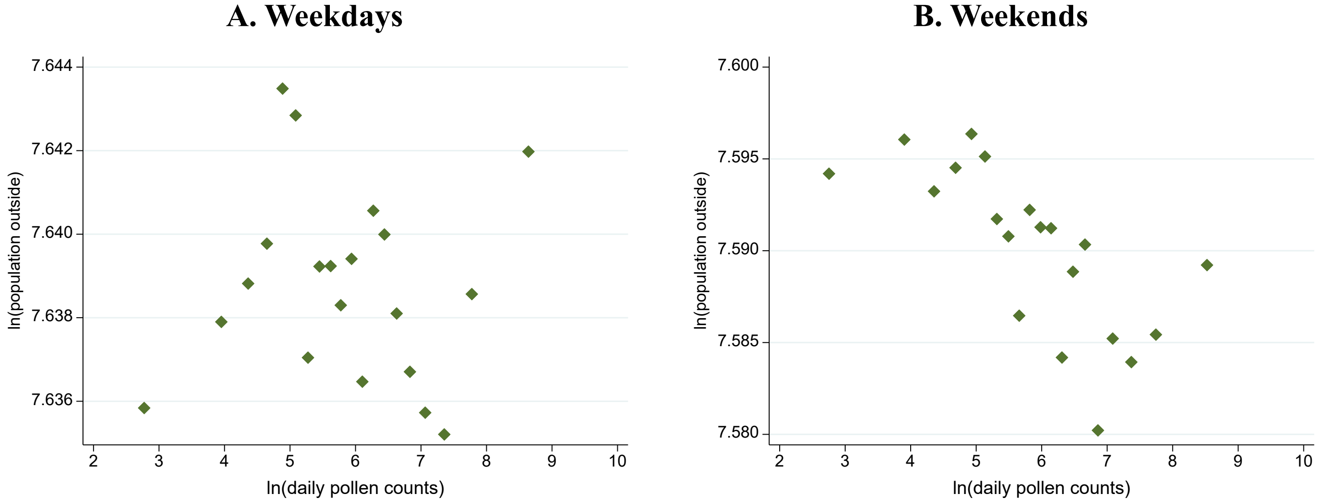
Notes: The sample is derived from attendance records from the three major zoos operated by the Tokyo Metropolitan Government and corresponding population estimates from cellphone mobility records for the period 2014 to 2019, with observations at the zoo per day level. The graphs display scatter plots illustrating the relationship between the logged daily attendance from admission records (on the *x*-axis) and the logged daily number of cell-phone–based population estimates at 2 p.m from location data (on the *y*-axis). Panels A–C present results for Ueno Zoo, Tama Zoological Park, and Inokashira Park Zoo, respectively. The correlations between the two variables in Panels A–C are 0.839, 0.756, and 0.673, respectively.

Figure G2—Pollen and zoo attendances in Tokyo



Notes: The sample is derived from admission records from the three major zoos operated by the Tokyo Metropolitan Government (Ueno Zoo, Tama Zoological Park, and Inokashira Park Zoo) for the period 2008 to 2019, with observations at the zoo per day level. The graphs display binscatter plots illustrating the relationship between the logged daily pollen counts (grains/m^3, on the *x*-axis) and the logged daily attendance (on the *y*-axis). The specification control for zoo and date fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and the logged average daily admissions for each zoo. Estimates are weighted by the average daily admissions in each zoo.

Figure G3—Pollen and avoiding going out



Notes: The sample is derived from cellphone mobility records for the period 2014 to 2019, with observations at the unit per day level (N= 343,454 for panel A and 135,399 for panel B). There are a total of 705 emergency response units. The graphs display binscatter plots illustrating the relationship between the logged daily pollen counts (grains/m^3, on the *x*-axis) and the logged daily number of people outdoors at 2 p.m. (on the *y*-axis). Panels A and B examine weekdays and weekends, respectively, controlling for month-by-year, month-by-prefecture, and day-of-week fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population in each unit.

Table G1—Avoid attending zoos

	(1)	(2)	(3)	(4)	(5)
	All	Weekdays	Weekends	Paid	Free
ln(pollen counts)	-0.0332***	-0.0222*	-0.0473***	-0.0175	-0.0705***
	(0.0095)	(0.0120)	(0.0130)	(0.0161)	(0.0124)
R-squared	0.95	0.95	0.96	0.90	0.93
N	3,474	2,333	1,141	3,425	3,474
Zoo FE	X	X	X	X	X
Date FE	X	X	X	X	X

Notes: The sample is derived from admission records from the three major zoos operated by the Tokyo Metropolitan Government (Ueno Zoo, Tama Zoological Park, and Inokashira Park Zoo) for the period 2008 to 2019, with observations at the zoo per day level. The dependent variable is the logged daily attendance. Column (1) encompasses all days, while Columns (2) and (3) separately report estimates for weekdays and weekends. Columns (4) and (5) distinguish between paid and free admissions. The specification control for zoo and date fixed effects, alongside weather covariates (precipitation, temperature, wind speed), darkness, and the logged average daily admissions for each zoo. The average daily admissions in each zoo weight estimate. Robust standard errors are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table G2—Avoiding going out and accidents

	All	Weekdays	Weekends
	(1)	(2)	(3)
ln(outdoor population)	0.960**	0.465	2.007**
	(0.418)	(0.441)	(0.775)
R-squared	0.49	0.48	0.51
N	478,853	343,454	135,399
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-by-year FE	X	X	X
Prefecture-by-month FE	X	X	X

Notes: The sample is derived from the ambulance records for the period 2014 to 2019, which are matched with "Mobile Spatial Statistics" data provided by NTT DOCOMO, Inc. at the unit-day level (N= 478,853). A total of 705 emergency response units are available. We present estimates from regressing daily accidents per million people (our primary outcome) on the logged outdoor population, employing the same sets of fixed effects and controls as in equation [1], except for the logged number of pollen counts. Standard errors clustered at the pollen monitoring station level are reported in parentheses. Columns (2) and (3) restrict the samples to weekdays and weekends, respectively. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table G3—Avoiding going out with full covariates

Outcome: logged outdoor population

	A. All	B. By type of day	
		Weekdays	Weekends
	(1)	(2)	(3)
ln(pollen counts)	-0.0005	0.0000	-0.0021***
	(0.0006)	(0.0006)	(0.0007)
Rainfall (base: no rainfall)			
<1 mm	-0.0061***	-0.0059***	-0.0047**
	(0.0013)	(0.0011)	(0.0019)
1 mm≤ & <2 mm	-0.0167***	-0.0144***	-0.0208***
	(0.0035)	(0.0024)	(0.0080)
≥2 mm	-0.0167***	-0.0150***	-0.0249***
	(0.0045)	(0.0041)	(0.0082)
Mean temperature (base: <0 ℃)			
[0, 5) ℃	0.0018	0.0068**	0.0096
	(0.0033)	(0.0034)	(0.0064)
[5, 10) ℃	0.0111***	0.0139***	0.0189***
	(0.0036)	(0.0037)	(0.0067)
[10, 15) ℃	0.0089**	0.0120***	0.0160**
	(0.0043)	(0.0043)	(0.0070)
[15, 20) ℃	0.0061	0.0094*	0.0172**
	(0.0045)	(0.0049)	(0.0068)
[20, 25) ℃	0.0120***	0.0165***	0.0200***
	(0.0043)	(0.0046)	(0.0069)
≥ 25 ℃	0.0273***	0.0264***	0.0319***
	(0.0057)	(0.0066)	(0.0079)
Mean wind speed	-0.0022***	-0.0021***	-0.0023***
	(0.0005)	(0.0005)	(0.0007)
Darkness	-0.0084***	-0.0090***	-0.0073***
	(0.0014)	(0.0012)	(0.0023)
ln(population)	1.3108***	1.2630***	1.4497***
	(0.1975)	(0.1997)	(0.2074)
R-squared	0.98	0.99	0.99
N	478,853	343,454	135,399
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-by-year FE	X	X	X
Prefecture-by-month FE	X	X	X

Notes: The sample is derived from cellphone mobility records from February to May for the period 2014 to 2019, with observations at the unit per day level. There are a total of 705 emergency response units. Estimates from the variant of equation [1] are reported along with standard errors clustered at the pollen monitoring station level in parentheses. The dependent variable is the logged daily outdoor population at 2 p.m. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table G4—Avoiding going out: Heterogeneity

Outcome: logged outdoor population

	A. Weekdays				B. Weekends			
	Non-elderly	Elderly	Male	Female	Non-elderly	Elderly	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(pollen counts)	-0.0007	0.0005	-0.0005	-0.0000	-0.0029***	-0.0013	-0.0025***	-0.0025***
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0009)	(0.0009)	(0.0008)	(0.0009)
Rain (base: no rain)								
<1 mm	-0.0050***	-0.0121***	-0.0026**	-0.0104***	-0.0032	-0.0111***	-0.0019	-0.0086***
	(0.0011)	(0.0016)	(0.0011)	(0.0013)	(0.0020)	(0.0027)	(0.0019)	(0.0023)
1 mm≤ & < 2 mm	-0.0089***	-0.0283***	-0.0051**	-0.0220***	-0.0170**	-0.0365***	-0.0115	-0.0317***
	(0.0020)	(0.0040)	(0.0023)	(0.0027)	(0.0077)	(0.0122)	(0.0073)	(0.0094)
≥ 2 mm	-0.0095**	-0.0334***	-0.0043	-0.0271***	-0.0162*	-0.0466***	-0.0144**	-0.0332***
	(0.0042)	(0.0057)	(0.0041)	(0.0048)	(0.0086)	(0.0095)	(0.0072)	(0.0100)
R-squared	0.97	0.97	0.98	0.98	0.97	0.97	0.98	0.98
N	341,433	340,495	341,093	341,343	134,450	134,140	134,409	134,387
Unit FE	X	X	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X	X	X
Month-by-year FE	X	X	X	X	X	X	X	X
Prefecture-by-month FE	X	X	X	X	X	X	X	X

Notes: The sample is derived from cellphone mobility records from February to May for the period 2014 to 2019, with observations at the unit per day level. There are a total of 705 emergency response units. Estimates from equation [1] are reported along with standard errors clustered at the level of pollen monitoring station in parentheses. The dependent variable is the logged daily outdoor population at 2 p.m. In addition to the FEs and weather covariates outlined in the table, average wind speed, darkness, and logged population are also included. The elderly category comprises individuals aged 60 years and older, while the non-elderly category encompasses everyone else. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Appendix H: Data Appendix

Data	Source
Ambulance records	Years: 2008–2019 (detailed diagnosis information is available from 2015 onwards) Data description: ambulance records archive Source: Fire and Disaster Management Agency (FDMA) of the Ministry of Internal Affairs and Communications https://www.fdma.go.jp/en/post1.html
Police records	Years: 2019–2020 Data description: traffic accident records of accidents involving injuries or deaths Source: National Policy Agency (NPA) https://www.npa.go.jp/publications/statistics/koutsuu/opendata/index_opendata.html
Pollen	Years: 2008–2019 Data description: hourly pollen counts from 120 stations, as well as hourly rainfall, temperature, wind speed, and wind direction from nearby weather stations during the pollen season (February to May except for Hokkaido, where the pollen season is March to June). Source: Ministry of the Environment (MOE), Pollen Monitoring System "Hanako-san" https://tenki.jp/pollen/ *Note*: MOE terminated data collection of pollen counts in 2021.
Temperature	Years: 2008–2019 Data description: hourly temperature (outside of the pollen season) Source: Japan Automated Meteorological Data Acquisition System (AMeDAS) operated by the Japan Meteorological Agency (JMA) https://www.data.jma.go.jp/obd/stats/etrn/
Pollution	Years: 2009 April–2019 March Data description: hourly SO_2, NO, NO_2, CO, OX, PM_{10} Source: National Institute for Environmental Studies https://www.nies.go.jp/igreen/index.html
Google Trends data	Years: 2016–2019 Data description: Google search index reflecting search term popularity for selected keywords, ranging from 0 to 100 in a given prefecture and day, proportional to total searches within the period.
Twitter data	Years: 2016–2019 Data description: the number of tweets that contain the selected keywords
Retail scanner data	Years: 2012–2019 Data description: called "Quick Purchase Report," which is the daily panel of purchase records from roughly 30,000 monitors Source: Macromill, Inc https://www.macromill.com/service/digital-data/consumer-purchase-history-data/ (in Japanese)
Cellphone mobility records	Years: 2014–2019 Data description: called "Mobile Spatial Statistics" data, which are estimates based on the location information of 85 million NTT DOCOMO cellphone users (as of March 2022) Source: NTT DOCOMO, Inc https://mobaku.jp/ (in Japanese)