“Invisible Killer”: Seasonal Allergy and Accidents[*]

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Abstract

Despite at least 400 million seasonal allergy sufferers worldwide, the adverse effects of pollen on “non-health” outcomes, such as cognition and productivity, are surprisingly understudied. Using the ambulance archives in Japan, we are the first to demonstrate that high pollen days are associated with the increased occurrence of accidents and injuries—one of the most extreme consequences of cognitive impairment. Using geolocation data, we find limited evidence of avoidance behaviors, implying that such risk is severely discounted. Finally, the increased pollen concentrations due to climate change are projected to increase pollen-induced accidents, with a minimum social cost of USD236 million annually.

Keywords: Seasonal allergy, Pollen, Accidents, Cognition, Avoidance behaviors, Adaptation, Climate change
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1. Introduction

"Hay fever," or seasonal allergic rhinitis (SAR) as it is medically known, is a common chronic condition induced by exposure to airborne allergens such as pollen and dust. SAR affects up to 30% of the population in developed countries, with an estimated 400 million sufferers worldwide (Greiner et al. 2011; Schmidt 2016). Despite its widespread global prevalence, the adverse impact of pollen has to date received surprisingly little attention from economist, probably due to the following reasons. First, the symptoms of SAR are relatively mild and chronic, including a runny nose, nasal congestion, sneezing, and itchy eyes. However, the non-acute physiological effects of pollen exposure can be potentially problematic since most people do not engage in serious avoidance behaviors to limit their exposure.

Second, in sharp contrast with *man-made* air pollution, the scope of governmental policy intervention for damage caused by *natural* sources, like pollen, is seemingly limited.[1] However, a recent study projects that global warming will accelerate pollen production and thus increase pollen concentrations (16 to 40%) and prolong the duration of pollen seasons (by 19 days) in the United States (Zhang and Steiner 2022). Figure 1 demonstrates the strong positive association between pollen counts and maximum temperature (Panel A) and the number of hot days above 30℃ (Panel B) in the previous summer in Japan—our study setting. Therefore, climate change caused by human activities can exacerbate the potential damage arising from naturally occurring pollen production.

In addition to the apparent negative health consequences, clinical studies have identified the detrimental effects pollen exposure has on cognitive performance in the form of decreased attention span and increased reaction time (Wilken et al. 2002). However, the existing studies of seasonal allergy on "non-health" outcomes such as cognition and productivity in the *field* setting are limited to its effect on the test performance of children (Bensnes 2016; Marcotte 2015, 2017).[2] We hypothesize that exposure to seasonal pollen has much broader consequences—beyond just children and test scores. Since pollen exposure severely inhibits cognitive functioning, any sensible daily activities that require continuous attention and performance, such as driving, can be affected.

[1] Economists gather knowledge on the impact of exposure to air pollution on a variety of outcomes ranging from health, human capital, labor productivity, and crime. See Graff Zivin and Neidell (2013) and Aguilar-Gomez et al. (2022) for summaries of the relevant literature.

[2] An exception is Chalfin et al. (2019) who document that violent crime *declines* in U.S. cities on days with unusually high pollen counts, potentially because people may spend less time outdoors on high pollen days.

We conduct the first investigation of the effects of acute and short-term pollen exposure on the incidence of accidents. These accidents include traffic accidents and work-related injuries, which are arguably some of the most extreme consequences of cognitive impairment. Driving safely is a complex and cognitively demanding task, and past studies document that cognitive performance is negatively correlated with the likelihood of motor vehicle accidents occurring (Anstey et al. 2005, 2012). Similarly, workplace injuries are most commonly caused by distractions (European Commission 2009).

We combine the data on pollen counts with the newly available administrative ambulance records that cover the universe of accidents that took place during the period 2008 to 2019 in Japan. These accidents are especially severe as they require ambulance transportation to hospitals. Japan is the ideal setting to conduct such research as the pollen monitoring stations are densely located across the country at a rate 42 times higher than those in the United States. The intensity of pollen concentration varies widely across spaces and time, allowing us to accurately measure pollen exposure as well as examine the potential non-linear dose responses. Furthermore, we are able to provide nationally representative estimates, unlike the samples in previous studies that are limited to only a handful of schools or districts near pollen stations. This assists in mitigating concerns about the generalizability of our findings. We leverage daily-level spatial and temporal variation in pollen counts of differing magnitudes to identify the effect of pollen exposure on accidents.

There are four primary findings. First, we find that high daily pollen counts are associated with increased accidents of all types, including traffic accidents—which account for more than one-third of all accidents, work-related injuries, sports injuries, and accidents involving fire. We document important heterogeneous responses to pollen exposure. While the effects are more pronounced for less severe accidents, elevated pollen exposure also increases accidents that lead to death. Interestingly, we find larger effects on the weekends than on the weekdays, suggesting limited avoidance behaviors on the weekend when most individuals should have more freedom to avoid exposure (e.g., remaining indoors) than they do on weekdays.

Second, we indeed find limited evidence of the existence of short-term avoidance behaviors to reduce pollen exposure. Since pollen size is relatively large ($\approx 30\ \mu m$), unlike PM2.5, the most effective and low-cost solution is simply staying indoors on high pollen days. Using geolocation data collected from Japan's largest mobile phone carrier companies, we discover a very small reduction in outdoor activities on high pollen days. This finding is in sharp contrast with the case of ambient pollution, where avoidance behaviors substantially mitigate the adverse effect of pollution on respiratory hospital admissions for the elderly and children (Neidell 2009).

Third, we fail to find strong evidence of medium-term adaptation potential to the adverse impact of pollen exposure. The fundamental question relating to environmental hazards is whether such hazards are mostly unavoidable or whether individuals can adapt by utilizing current technologies.[3] In our context, newer medications for seasonal allergies have fewer side effects and lower chances of drowsiness being a side effect, which might reduce the risk of drowsy driving, for instance. In addition, one may have more time to engage in defensive investments such as the purchase of an air purifier. We investigate whether the detrimental effects of pollen exposure have declined significantly in more recent years, and we fail to find such evidence, at least within the window of 12 years, which makes up our sample period. Furthermore, we find that individuals who live in the high-average pollen regions have similar pollen-induced accident rates as those who live in the low-average pollen regions, corroborating the previous findings.

Finally, we combine our estimates of pollen on accidents with projections of future climate as well as the relationship between the temperature and pollen counts obtained in Figure 1 to illustrate the magnitude of the social cost of anthropogenic climate change. The "business as usual" scenario from the Intergovernmental Panel on Climate Change (IPCC)—which predicts an increase of 4.1°C in the summer temperature in the years 2076–2095 in Japan—would lead to 1,823 additional pollen-induced accidents annually. Multiplying the resulting accident counts with the average accident costs, the expected annual social cost of pollen-induced accidents is on the order of approximately $236 million. This estimated social cost is very likely to be lower bound since we fail to take into account the accidents at both sides of severity distribution (i.e., minor cases as well as immediate deaths) that do not require ambulance transportation to hospitals.

This paper has several policy implications. First, we demonstrate that pollen exposure can affect much more than the school performance of children and might have a wider impact on cognition, productivity, and daily activities than is previously considered. For instance, an increase in workplace injuries we find suggests that labor productivity, in general, should be undermined. Therefore, the current estimated cost of exposure to airborne allergens, which is based mainly on easy-to-measure health outcomes, school days missed, and work

[3] The current evidence presents the significant adaptation potential in the context of mortality to heat exposure (Barreca et al. 2016; Heutel et al. 2021; Mullins and White. 2020), infant mortality to dust (Adhvaryu et al. 2022), with mixed evidence for workplace injuries to heat (Dillender 2021; Park et al. 2021).

absenteeism, may severely underestimate the true cost to society.

Second, the limited short-term avoidance behaviors, despite easy access to detailed information relating to daily pollen levels, indicate that the adverse cognitive effects of pollen exposure are severely discounted. Real-time pollen information is commonly reported in the weather forecast on TVs and in newspapers, and many apps and websites also provided pollen forecasts during our sample period. Thus, government intervention that raises the awareness of the risk (i.e., salience) that pollen exposure poses to health and cognition might be necessary, in addition to the provision of timely pollen information. For example, public information campaigns, such as "pollen alert"—recommending curtailing outdoor activities, wearing particulate-filtering masks, and taking public transportation on high pollen days due to elevated risk—could be a possibly cost-effective tool to reduce pollen-induced accidents.

Third, while much of the literature on climate change has focused on the impact of rising temperature on direct outcomes such as aggregate incomes, mobility, mortality, and agricultural outcomes (Carleton and Solomon 2016; Dell et al. 2014), the increase in seasonal allergy sufferers and the associated performance impairment could be the indirect and undiscovered cost of anthropogenic climate change. Consequently, any measure to mitigate the risk of a warming climate could have substantial social benefits by preventing temperature-driven increases in airborne pollen.

The rest of the paper is organized as follows. Section 2 briefly describes the background. Section 3 describes the data, following which Section 4 presents the econometric model. Section 5 reports the findings of this study, and Section 6 offers conclusions.

2. Background

2.1. Pollen and seasonal allergy

SAR, widely known as "hay fever," is a common chronic condition. SAR occurs when an individual's immune system reacts to allergens in the air, such as pollen and dust, causing the immune system to produce antibodies (such as histamines and cytokines) to fight the perceived threat from the pollen grains. The antibodies, in turn, cause inflammation in the airways, inducing various allergic symptoms, such as a runny nose, nasal congestion, sneezing, and itchy eyes (Greiner et al. 2012).

SAR is a global health problem as otherwise seemingly healthy individuals can be affected by SAR (Bousquet et al. 2008). The prevalence rates vary by country but are generally between 10 and 40% in developed countries, with an estimated 400 million sufferers worldwide (Greiner et al. 2011; Schmidt 2016). This number is likely to underestimate the true prevalence rate as some individuals do not seek medical assistance for the condition. Furthermore, numerous studies document increasing prevalence due to various factors such as urbanization, westernization of lifestyles, and climate change.

Japan is not an exception. An extensive epidemiological survey for otolaryngologists and their families has been conducted every ten years (1998, 2008, and 2019) and has been guided by the Japan Society of Immunology and Allergology in Otolaryngology. According to this study, the prevalence rate of SAR has steadily increased by roughly 10 percentage points every ten years: from 19.6% in 1998 to 29.8% in 2008 and further to 42.5% in 2019. The prevalence rate has been found to peak around middle age, but a substantial number of young and older individuals also suffer from SAR (Matsubara et al. 2020).[4] In addition, the prevalence rate is generally high in urban areas, and in Tokyo, it increased from 19.4% in 1996 to approximately 48.8% in 2016. This means that in 2016 almost half of the residents in Tokyo suffered from SAR (Tokyo Metropolitan Institute of Public Health 2017).

Due to the relatively mild and chronic symptoms associated with SAR, its economic cost has been overlooked. In addition to direct medical costs (e.g., medications and emergency department visits), past studies suggest that pollen allergies are a major source of absenteeism from work and school (Hellgren et al. 2010; Lamb et al. 2006). Arrighi et al. (1996) estimate that schoolchildren in the United States lose around 2 million school days per year due to allergic symptoms from pollen. These symptoms include lack of sleep, somnolence during the day, and concentration difficulties.[5]

Most relevant to this study, clinical studies have identified the negative effect of SAR on cognitive performance. This often occurs indirectly as a result of deteriorated sleep quality (Craig et al. 2004; Santos et al. 2006) and directly by antibodies themselves via brain function (McAfoose and Baune 2009). For instance, Wilken et al. (2002) found that allergic adults who were randomly exposed to pollen performed worse on a broad range of cognitive measures than those who had not been exposed. Those adults who were exposed to the pollen exhibited longer response times, reduced working memory, divided attention, and slower computation. Unfortunately, medical studies have shown that allergy medications can induce similar or even worse effects on cognitive functioning due to various side effects, such as

[4] The prevalence rates of SAR in 2019 are 30.1% (ages 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).
[5] A few studies have estimated the annual per capita cost of SAR to be in the range of $600 to $1,000, considering direct medical costs and indirect costs due to absenteeism (Hellgren et al. 2010; Lamb et al. 2006).

drowsiness, dry mouth, and lethargy (Jáuregui et al. 2009; Kay 2000). It should be noted that our analysis shows the *reduced* form relationship between the pollen concentration and the number of accidents, including the side effect of the medication for seasonal allergies.[6]

To date, the existing studies of seasonal allergy on cognition and productivity in the *field* setting have been limited to its effect on the test performance of children (Bensnes 2016; Marcotte 2015, 2017). However, since pollen exposure impairs cognitive performance, almost any daily activities can be severely affected. In this paper, we focus on accidents, including traffic collisions and work-related injuries, as they involve the most extreme forms of performance impairment. For example, it is well established that cognitive function is negatively correlated with the likelihood of motor vehicle accidents (Anstey et al. 2005, 2012).[7] Based on the randomized control with 19 patients with documented allergic rhinitis (AR) history, Vuurman et al. (2014) argue that the magnitude of the impairing effects of AR on driving is almost comparable to the effects of a blood alcohol contents (BAC) of 0.05%, which is the legal limit in many countries.

In sum, while scientific knowledge concerning the impact of other environmental stressors (such as pollution and temperature) on cognitive performance and productivity has been gathered[8], the impact of airborne pollen and associated seasonal allergies on these outcomes has yet to be sufficiently examined.

2.2. Warming climate and pollen

Since temperature and carbon dioxide (CO_2) concentrations have been found to increase pollen production, climate change is expected to impact pollen concentrations and the duration of pollen seasons significantly. Anderegg et al. (2021) tracked pollen trends across 60 pollen stations in the United States from 1990 to 2018 and found increases of 20.9% and 21.5% in annual and spring (February–May) pollen concentrations, respectively, as well as an advance of 20 days in the pollen season start date and a lengthening of the pollen season by eight days. Importantly, Anderegg et al. (2021) conducted a model selection analysis to identify the main drivers of pollen proliferation and found that among eight climate variables

[6] Therefore, we are not able to distinguish the relative importance of various potential mechanisms for which there is clinical evidence of links to pollen exposure, such as cognition, concentration, mood, fatigue, emotion, or physical distractions.
[7] Smith (2016) also demonstrates that a one-hour sleep loss increases the probability of being in a drowsiness-related fatal motor vehicle accident by 46%.
[8] See for example: pollution (e.g., Chang et al. 2016, 2019; Ebenstein et al. 2016; Graff Zivin and Neidell 2012; He et al. 2019; La Nauze and Severnini 2021; Sager 2019; Zhang et al. 2018) and temperature (e.g., Adhvaryu et al. 2020; Colmer 2021; Park et al. 2021; Somanathan et al. 2021).

(including temperature, precipitation, frost days, and CO_2 concentrations), mean annual temperature is the strongest predictor of the above-mentioned pollen metrics. Increased pollen quantities, advancement of pollen season starting date, and prolonged duration of the pollen season have similarly been observed in Europe (D'Amato 2007; Ziello et al. 2012; Hamaoui-Laguel et al. 2015).

We confirm that such a relationship is also observed in the data we collected and analyzed in Japan. Figure A1 displays the times series of average daily pollen counts for the period February to May and the average maximum temperature (Panel A) as well as the number of days where the temperature exceeds 30℃ (Panel B) in July and August in the *previous* summer, using station-year panel data from all the pollen monitoring stations (N= 120) during the period 2008 to 2019. Pollen counts are expressed in (24-hour cumulative) particles per cubic meter of air (grains/m^3). Both graphs show a clear positive relationship between the temperature in summer and the pollen counts in the following spring. For example, a cold summer was experienced in 2009, and the pollen concentration in the spring of 2010 was relatively low. On the contrary, quite a hot summer was experienced in 2010, and high pollen counts were observed in the spring of 2011.

Figure 1, mentioned in the introduction, sets out the associations between pollen counts and temperatures of 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 an increase of 1℃ in the maximum temperature in the previous summer is associated with an average additional 167 grains/m^3 daily pollen count in the following spring. Since 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 may be considerable. Similarly, the slope in Panel B is 23.7 (t-stats= 11.2), indicating that a sum of 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.

To summarize, the evidence thus far indicates that climate change caused by human activities has already increased the intensity of pollen seasons in different parts of the world. The expected temperature rise due to global warming is likely to exacerbate this issue further and intensify this trend in the coming decades (Anderegg et al. 2021; D'Amato 2007; Ziska et al. 2019). For instance, in a recent study conducted by Zhang and Steiner (2022), they project that climate change will *further* hasten the arrival of the pollen season (by up to 40 days), prolong the duration of the pollen season (by approximately 19 days), and, as a result, increase the annual total pollen emission (by 16 to 40%) in the United States.

3. Data

We combine the daily airborne pollen counts with newly available administrative data that reports on accidents from ambulance records for the period 2008 to 2019 in Japan. To our knowledge, we are the first to make use of this dataset for economic research. The details in respect of the data sources are provided in Appendix Section F.

3.1. Airborne pollen

We obtain data in respect of airborne pollen from the Japanese Ministry of the Environment's pollen monitoring system (designated "Hanako-san"), which provides hourly readings of pollen counts (grains/m^3) for Japanese cedar and hinoki cypress (Yamada et al. 2014). Figure A2 displays the calendar of pollen season for typical plants, showing that these two types of plants are the primary source of pollen production in Japan, mainly from February to May. Comprehensive data on pollen counts are available from 2008. This information is automatically published on the Ministry of the Environment's website. In addition, during the pollen season, the pollen level is commonly reported in the weather forecast, along with the usual temperature and precipitation. See Figure A3 for real-time and forecasted pollen levels reported on TV on a typical day during the pollen season in Japan. Thus, the cost of acquiring such information is nearly zero.

There are a total of 120 pollen monitoring stations located nationwide in Japan. Figure A4 displays the locations of all monitoring stations as of 2019.[9] Each of the 46 prefectures has, on average, two to three monitoring stations, placed both in urban areas with high population densities and in mountainous regions that are the major source of pollen production (Wakamiya et al. 2019).[10] The number of pollen monitoring stations is extremely high, given the size of the country. For example, the United States—which is 26 times larger than Japan—has only 74 pollen monitoring stations nationwide. This suggests that the density of pollen stations is *42 times* higher in Japan than it is in the United States.

[9] The number of pollen stations has remained 120 since 2008, and thus our estimates are not affected by the increase or decrease of monitoring stations. The movement of monitoring stations is limited to a handful of stations, and the distance of movement is very small.

[10] Okinawa prefecture, which is the southernmost remote island in Japan, with a different climate from the rest of Japan, has no pollen station, as little pollen is observed. We exclude Okinawa from the entire analysis, leaving 46 prefectures.

Since typical pollens in Japan can be distributed more than 100 km (160 miles) away and remain in the air for more than 12 hours, almost entire areas of Japan, even in sparsely forested cities, can be contaminated by airborne pollens (Yamada et al. 2014). Figure A5 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 explained in Section 3.2). The mean and median distances from pollen stations are 25.4 and 17.5 km, respectively. Even with a conservative threshold of 48 km (30 miles) for pollen measurements to be valid (Chalfin et al. 2019), 90.2% of all municipalities are within this threshold.[11]

The high density of stations across the country enables us to (i) accurately measure the exposure to pollen, (ii) provide nationally representative estimates of pollen exposure (unlike previous studies that are limited to a handful of schools or districts near pollen stations), and (iii) include the continuous pollen exposure variable with differing magnitudes as the regressor to investigate the potential non-linearity in dose-response (unlike past studies that only included a dichotomous variable that defined high pollen days).

Since the pollen emission from the Japanese cedar (the main pollen-producing plant) starts in February and peaks in March to April (as shown in Figure A2), the pollen count is monitored from February to May every year.[12] We aggregate the monitor readings to obtain the daily level by adding up the hourly observations to calculate the accumulated number of pollen grains counted in 24 hours. In addition, weather covariates from nearby weather stations are included in the same data. In particular, hourly temperature, precipitation, and wind speed are recorded. Similarly, we aggregate these variables to obtain the daily level.

3.2. Ambulance records

Our data relating to accidents and injuries is derived from the Fire and Disaster Management Agency (FDMA) of the Ministry of Internal Affairs and Communications, Japan. The data covers the universe of ambulance calls for the period 2008 to 2019 that result in ambulance transportation to hospitals. The registration of all ambulance records in the online system of FDMA became mandatory in 2008. Since ambulance service is publicly provided free of charge in Japan, there is no differential selection into the sample by socioeconomic status. This setting contrasts sharply with the countries like the United States,

[11] Chalfin et al. (2019) made use of the criminal records from stations within 30 miles (48 km) of the city center, while the National Allergy Bureau (NAB) suggests that pollen measurements are valid within a 20-mile (32 km) radius of each station.
[12] The exception is Hokkaido prefecture which is located far north (with four stations), and thus the monitoring period is delayed by one month (March to June).

where the cost of an ambulance ride is not usually free, and thus ambulance use varies by health insurance status or income (Meisel et al. 2011).

A total of 14.7 million accidents that required ambulance rides were recorded for the period 2008 to 2019, with a yearly average of 1.2 million accidents.[13] The data provide detailed information in respect of individual accidents. We have information on the location the accidents took place, the exact date and time of the ambulance calls, the type of accidents, the severity of injuries, age, and gender of those involved in the accidents.

Two features of this dataset are particularly beneficial for our study. The first unique feature is that we have knowledge of the type of accidents which had occurred, including traffic accidents, work-related injuries, sports injuries, and accidents involving fire. Traffic accidents are of particular interest to us as they are the second leading cause of accidental deaths (after asphyxia), with a recorded average of over 4,000 and 700,000 annual fatalities and injuries, respectively, for the period 2008 to 2019 (MHLW 2009; NPA 2022), with 127 million total population in Japan. Given the high base level of traffic fatalities and injuries, even a small change in the risk of an accident being fatal is highly relevant to social welfare. Furthermore, these traffic accidents can cause negative externality even for those who do not suffer from seasonal allergies but are involved in the accidents. Similarly, work-related injuries are also worth investigating as an increased risk of workplace injuries may cause a decrease in labor productivity. Broten et al. (2019) find that workers who are injured on the job face a subsequent earnings penalty of 8% on average, and this increases to 30% for those who are permanently disabled.

Another distinctive feature of the dataset we utilized is that it includes information on the severity of injuries sustained. This measure is expected to be very accurate as it is based on the initial clinical assessment by the doctors who first attend to the injured person at the time of hospital admission. The severity measure ranges from death/fatal, serious, moderate, to light, where “serious” accidents require more than three weeks of hospitalization and treatment; “moderate” requires hospitalization, but for less than three weeks, and “light” does not require hospital admission. Two key advantages of ambulance records versus vital statistics are that we are able to capture non-fatal, but severe injuries that would be missed in vital statistics and that we are able to capture the accidents that occurred on the day without

[13] The ambulance records also include emergency cases due to illness (72.3% of all records). Since our focus is on accidents, we extract data on five types of accidents from the ambulance archives, namely, traffic accidents, work-related injuries, sports injuries, accidents involving fire, and other accidents, which add up to 25.9% of all records. The remaining records relate to self-injurious activities, assault, drowning, natural disasters, and other categories (1.8%).

measurement errors, unlike vital statistics, which may record some accidental deaths with delays.

The geographical unit in ambulance records is an emergency response unit (hereinafter referred to as "unit"), which is the level of ambulance service in Japan. While many units are municipalities themselves, some small municipalities form a unit to increase the efficiency of the 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 the accident records to the unit-day level by adding up the hourly observations within the units.[14]

3.3. Sample construction and summary statistics

To construct our primary sample, we merge unit-day level ambulance records with the same-day daily level pollen counts from the nearby monitoring stations. Thus, the primary sample comprises records and counts from February to May (i.e., high pollen seasons only) for all prefectures except for Hokkaido, which spans from March to June for the period 2008 to 2019.

Table 1 presents summary statistics for our primary estimation sample, which consists of 970,309 unit-day observations. On average, there are 33 daily accidents per million people. Traffic accidents are the leading type of accident which accounted for 37.6% of all accidents. This is followed by work-related injuries (3.5%), sports injuries (2.6%), and accidents involving fire (0.5%). The other accidents which do not belong to any of these categories accounted for over half of all accidents (55.8%).[15] Traffic accidents and other accidents together make up nearly 90%.

The mean daily concentration of airborne pollen is 984 grains/m^3 (with a standard deviation of 2,135). Figure A6 plots the daily pollen counts for five selected locations from the north to the south of Japan, demonstrating substantial variations in pollen concentration across space and time. Since pollen counts are rightly skewed, we take the natural log of pollen counts as the main regressor throughout the study unless otherwise mentioned. Panel

[14] The timestamp of each accident reflects the time at which the accident is reported to emergency response units rather than the actual time that the accident occurred. This might result in some degree of measurement error in terms of the hour (more likely) than the date (less likely). As a result, we aggregate accidents to the daily level, following the existing literature (e.g., Herrnstadt et al. 2021; Park et al. 2021).

[15] For example, these accidents include: (i) slipping on a step on the road and falling down, (ii) slipping on a snowy road and falling down, (iii) spilled pot and getting burned, and (iv) slamming a finger in a screen door, ranging from minor accidents to major ones.

A of Figure A7 displays the histogram of logged daily pollen counts during the period 2008 to 2019, while Panel B displays the same counts after residualized by the unit, month-by-year, month-by-prefecture, and day-of-the-week FEs. This figure demonstrates substantial residual variation in pollen concentrations, indicating ample variation for obtaining precise estimates.

4. Econometric model

We estimate the effect of short-run exposure to pollen on the number of accidents, net of any potentially confounding factors:

$$Y_{idmy} = \beta \log\left(Pollen_{idmy}\right) + \gamma X'_{idmy} + \alpha_i + \alpha_{time} + \varepsilon_{dmy}, \quad [1]$$

where the dependent variable Y_{idmy} is the number of accidents per million people in the unit i on day d in month m and year y. The logged form of the main regressor (pollen counts) is consistent with the non-linearity in dose-response in the clinical studies (Erbas et al. 2007).[16] We later show the results from the alternative specifications (e.g., level-level or "dose-response") or Poisson model to account for the count nature of the accidents and assess the sensitivity of our results to zero observations. The parameter of interest is β, which measures the change in the outcome associated with a 100 percent increase in pollen counts. Unit fixed effect (α_i) controls for geographic differences in health and pollen concentrations.

The high granularity of our data allows us to include 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-the-week FEs (Deryugina et al. 2019). We later replace these with more or less stringent ones as a robustness check. Prefecture-by-month FE controls any seasonal correlation between pollen counts and accidents, allowing this correlation to vary by prefecture. The month-by-year FE control flexibly for nationwide time-varying shocks during our sample period. Finally, day-of-the-week FE accounts for within-week variation in accidents. In this way, we compare days in the same month in the same unit that happens to differ in pollen concentration, alleviating concerns that other seasonal trends in accidents could affect the results.

[16] We add one to account for zero pollen counts (0.83%) before taking the log. Later, we show that our results are robust to dropping these observations and taking logs without adding 1 in Table 3. Bensnes (2016) and Marcotte (2017) also take the log form of pollen counts.

The X'_{idmy} flexibly control for daily variation in weather covariates. We include seven indicators for 5℃ intervals of daily average temperatures, ranging from 0℃ or less to 25℃ 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 unobserved factor for traffic accidents (Bünnings and Schiele 2021). Finally, we control the logged population, which is related to population density and congestion (once with unit FE included), potentially affecting the risk of accidents (Abouk and Adams 2013). The underlying assumption is that once we control for the series of location and time fixed effects as well as weather covariates, temporal, seasonal, and geographic variations in daily pollen counts would be considered as good as random. This assumption is arguably plausible with the very granular sets of fixed effects and daily variation in pollen counts from naturally occurring processes.

We cluster all standard errors at the pollen monitoring station (N= 120)—the level of underlying variation in our treatment variable (Abadie et al. 2017)—to account for possible serial correlation and weight all estimates by the relevant population in cases where the dependent variable is in per capita terms.

5. Results

5.1. "First stage"—Symptoms of seasonal allergy

Before revealing our main findings, we would like to present evidence of a "first stage"—whether people are more likely to suffer from seasonal allergy symptoms on high pollen days than low pollen days, using data on both internet search activities (Google Trends) and social media posts (Twitter data). All detailed results in this subsection can be found in Appendix Section B.

We first use publicly available Google Trends data and collect data on three broad categories: (1) pollen-related keywords, (2) symptoms-related keywords, and (3) leading brand names of allergy medications in Japan during the period 2016 to 2019 at the prefecture-day level (N= 21,551). See Table B1 for the complete list of search keywords used. Google search index reflects search term popularity and takes the value of 0 to 100 in a given prefecture and on a given day in proportion to total searches within the search period.[17]

Figure 2 displays the results of symptoms-related keywords ("runny nose," "nasal congestion," "sneeze," and "itchy eyes" from Category 2 in Table B1). Panel A shows the time series of daily pollen counts (grains/m^3) and the Google search index for these keywords in 2018 as an example. They move closely over time. Panel B displays the binscatter plots of the relationship between logged daily pollen counts and search index after controlling for the prefecture, month-by-year, and day-of-the-week FE. The linear lines seem to fit the data well. Panel A of Table B2 shows that a 100% increase in daily pollen counts leads to increases in the search index by 3.6 on a 0–100 scale (with a mean of 30.4) in Column (1), and the results are robust to alternative sets of time fixed effects in the remaining columns (p-values<0.01). Similar patterns are observed for other keyword categories in the same table.

We replicate the same relationship between pollen counts and keywords using public Twitter data for the period 2016 to 2019 at the prefecture-day level.[18] The only difference from the above analysis is that the dependent variable is now the number of Tweets that contain the same three sets of keywords. Panels B of Figures B1, B2, and Table B2 demonstrate that people similarly tend to tweet these keywords more on high pollen days.

One advantage that Twitter data has over Google Trend data is that while the sample is more skewed to younger cohorts, people tend to express the status of their "feelings" in Tweets. Thus, in addition, we collect data pertaining to the number of Tweets related to sleep, namely, "having a hard time falling asleep" and "feeling sleepy," as clinical studies suggest that decreased sleep quality is one way in which pollen exposure worsens cognitive functioning (Craig et al. 2004; Santos et al. 2006). Figure B3 and Table B3 show that individuals seem to have more sleep-related issues on high pollen days. This "first stage" evidence reassures us that individuals do suffer from typical seasonal allergy symptoms that could give rise to accidents on high pollen days.

5.2. Basic results

Figure 3 displays the binscatter plots of the relationship between the logged daily pollen counts (grains/m^3) and the number of accidents per million people: all accidents (Panel A), followed by each type of accident by size (except for "other" accidents), namely, traffic

[17] The cutoff of 2016 is motivated by data completeness as well as the fact that Google made a change to its data collection system on January 1, 2016. We follow Brodeur et al. (2021) to construct daily-level Google Trends data across multiple years using overlapping periods of daily and weekly data.
[18] We assign prefecture based on the location at the time of the Tweet.

accidents (Panel B), work-related injuries (Panel C), sports injuries (Panel D), accidents involving fire (Panel E), and other accidents (Panel F) after controlling for the unit, month-by-year, month-by-prefecture, and day-of-the-week FEs. All figures display a relatively linear relationship, slightly flattening at a very high pollen concentration level. This simple plot of raw data (net of location and time FEs) already reveals a strong relationship between the pollen concentration and the number of accidents. We formally test this relationship below.

Table 2 reports the main estimates from Equation [1]. Column (1) indicates that a 10% increase in pollen count leads to an increase in the number of accidents by 0.0231 (0.231×0.1) per million people, which is precise and highly statistically significant (p-value<0.001, t-stats= 14.0). Columns (2) to (5) show that, while the magnitude varies by accident type, the elevated pollen concentration increases all types of accidents. In particular, while the share is small (3.5%), the increased incidence of work-related injuries indicates that labor productivity, in general, is likely to be affected by pollen exposure. Due to space considerations, we will focus on the categories: "all accidents" and "traffic accidents" from here on. We choose traffic accidents as they make up 37.6% of the accidents that occur. We discuss the monetary values of pollen-induced accidents in Section 5.7, where we project the potential damages from climate change.

Importantly, our estimates provide a very lower bound as the ambulance records analyzed do not include accidents on the extremes of the severity distribution, i.e., minor cases and immediate deaths, that do not require ambulance transportation to hospitals. In addition, the severity of injuries is assessed at the time of admission to hospital, and this may have led to an underestimation of eventual deaths.[19]

Dose-response—. Figure C1 plots the estimates from non-parametric binned regression to examine dose responses more flexibly. Specifically, logged daily pollen in Equation [1] is replaced by the dummies for each decile of daily pollen in *levels*. Panel A for all accidents reveals a clear concave relationship, suggesting that even low concentrations of pollen—which are more frequent than higher concentrations—may have a meaningful impact on cognitive performance and hence the incidence of accidents. This concave dose-response function also seems to indicate the benefits of reducing pollen concentrations even for

[19] For example, the number of work-related injuries leading to death that are recorded in our ambulance records for 2019 is 392, while the corresponding number reported to the Ministry of Health, Labour and Welfare (MHLW) is 845 (MHLW 2020). Similarly, the number of work-related injuries, including injuries of *all* severity levels in our ambulance records in 2019, is 50,578, while the total number of work-related injuries that result in either death or at least four days of work absenteeism reported to the MHLW is 125,611 (MHLW 2020).

countries with lower pollen levels than in our setting. In addition, the shape of the function explains why level-log specification in Equation [1] fits the data well.

5.3. Robustness

Our results on the effect pollen exposure have on accidents are robust to a battery of specification checks, including different types of location and time fixed effects, different ways of constructing regressors as well as outcomes, alternative specifications, and placebo exercises.

Robustness—. Table 3 provides the results of robustness checks and extensions. Our results are robust to different ways of constructing the pollen concentration, including an inverse distance weighting average of three nearby stations (Columns (2) and (3)), adding pollution covariates (Column (4))[20], limiting the sample to the units within 48 km from pollen monitoring stations to reduce the measurement errors (Column (5)), and an unweighted ordinary least square (OLS) (Column (6)). To address the possibility that the effect of pollen can potentially appear with lags, we extend the outcome window to the following day and then to the following two days (i.e., t and t+1, or t, t+1, and t+2) in Columns (7) and (8) of Table 3. These estimates are slightly larger than the contemporaneous effect in Column (1), implying that we may even have underestimated the effect of pollen exposure. The short-lived effect is not surprising as while pollen triggers an allergic reaction within minutes after SAR sufferers are exposed, its effects generally do not last more than four to eight hours (Skoner 2001).[21] Our results are also robust to aggregating data at the weekly level to net out any temporal displacement and capture dynamic effects that persist over the week in Column (9).

Table C1 illustrates that our estimates are robust to more or less stringent fixed effects, assuring that our results cannot be explained by specific unobserved seasonal or regional patterns. Table C2 also indicates that our results are robust to different clustering choices, including two-way clustering by both monitoring stations and dates to additionally account for possible spatial correlation or choosing broader geographical areas (46 prefectures) than pollen monitoring stations (120 stations). Table C3 shows that our results are robust to log-

[20] The correlation between pollen counts and other pollutants is as low as 0.02 (CO)-0.12 (PM10), allowing pollen to have an independent impact on the number of accidents that occur.

[21] The short-lived effect of pollen exposure is consistent with the previous literature documenting the short-lived impact of pollution exposure on health (e.g., Schlenker and Walker 2016), crime (e.g., Herrnstadt and Muehlegger 2021), and productivity (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019).

log specification or Poisson pseudo-maximum likelihood (PPML) model to account for the count nature of the accidents.

Placebo—. Table C4 falsely assigns the pollen levels of the exact day from the previous year or the next year in the same unit, finding much smaller and statistically insignificant results. Furthermore, Figure C2 displays the binscatter plots of the relationship between the logged daily pollen counts and the number of daily emergency ambulance transportation trips due to cancer. We find no discernable pattern as expected, which reassures us that our results are not driven by specific unobserved seasonal or regional patterns.[22]

Replication—. Traffic accidents are also recorded in police records, which cover all traffic accidents that result in personal injury and that are reported to the National Police Agency for the period 2019 to 2020 (see Appendix Section D for details on data). Table D1 compares the mortality estimates from traffic accidents using ambulance (our primary sample) and police records. While the estimate of pollen on mortality from traffic accidents using police records (p-value<0.01) is slightly larger than that of ambulance records, they are not statistically distinguishable from each other.[23] We are reassured that the effect of pollen exposure is robust to different samples collected by different government bureaus with potentially different definitions of traffic accidents, which strengthens the internal validity of our estimates.

5.4. Heterogeneity

Severity—. Figure 4 plots the estimates along with a 95% confidence interval for each severity level, separately for all accidents (Panel A) and for traffic accidents (Panel B). Panel A suggests that while the estimates become smaller as the severity level increases, all the estimates, including death/fatal, are positive and statistically significant. Panel B for traffic accidents shows similar patterns. Interestingly, the estimate relative to the mean is larger in death/fatal than any other severity level in the case of traffic accidents, suggesting that pollen exposure may lead to serious consequences.

Other heterogeneity—. The ambulance records also include other characteristics of the accidents and people involved. Using all accident samples, Figure 5 explores the heterogeneous treatment effect other than severity.[24] Panels A and B explore the

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[22] The ambulance records include detailed diagnostic information (equivalent to ICD10) from 2015 on.

[23] One potential reason for this observation is that the police records include all the deaths *within 24 hours* due to traffic accidents, unlike the ambulance records, which only includes deaths that occur at the time of admission to hospital.

[24] For completeness, the heterogeneity analysis for the traffic accidents is displayed in Figure C3.

heterogeneity by demographics, namely, age and gender. Overall, we find statistically significant effects in all age groups and both genders, with relatively similar magnitudes relative to the means, reported on the far right in the figure. Panel C examines the heterogeneity by location of accident occurrence. The increase in the occurrence of accidents even takes place when individuals are at home, indicating just how difficult it is for individuals to completely avoid outdoor pollens as they can remain on clothing (e.g., woolen coats) and are easily brought indoors. This may also reflect the lingering effect of outdoor pollen exposure.

Intriguingly, Panel D of Figure 5 shows that the effect of pollen exposure is statistically larger on weekends than on weekdays, even though most individuals should have more freedom to remain indoors and avoid exposure as non-mandatory trips can be canceled or rescheduled. This result suggests limited short-term avoidance behaviors. We explore this point further in the next subsection.

5.5. Short-term avoidance behaviors

Since the size of pollens is relatively large (≈30 μm) compared to much smaller particulates such as PM2.5, they are less likely to be able to enter houses. Thus, the temporal, but low-cost and effective means of reducing pollen exposure is simply to stay indoors and limit possibly pollen infiltration by closing windows and doors on high pollen days. We explore the role of avoidance behaviors more formally below.

Conceptual framework—. Let $Accidents = f(Pollen, Avoid(Pollen))$ where the number of accidents is the function of the level of pollen concentration ($Pollen$), and avoidance behaviors ($Avoid$) that are influenced by the pollen concentration. Following the notation from previous studies (e.g., Moretti and Neidell 2011; Neidell 2009), we can write the total derivative as follows:

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

where the “behavioral” or “reduced-form” effect (what we estimate so far) of pollen on accidents consists of the “biological” effect of pollen (first component of right-hand side (RHS) variable) which we *want* to estimate *and* the effect of avoidance behaviors (the second component of RHS). The latter is the product of the marginal return from avoidance behaviors $\left(\frac{\partial Accidents}{\partial Avoid} < 0\right)$, and the magnitude of avoidance behaviors in response to the level of pollen $\left(\frac{\partial Avoid}{\partial Pollen} > 0\right)$. Since the second component of RHS is supposed to be negative, the "behavioral" effect that already incorporates avoidance behaviors is *smaller* (i.e., underestimated) than that of the "biological" effect. For example, Neidell (2009) find that the "reduced-form" effect is 40% and 160% smaller for the elderly and children, respectively, than the pure "biological" effect.

Construction of mobility measure—. To investigate the extent of the avoidance behaviors $\left(\frac{\partial Avoid}{\partial Pollen}\right)$ in our context, we use geolocation data (called "Mobile Spatial Statistics" (MSS)) provided by NTT DOCOMO, Inc., Japan's largest mobile phone carrier. Based on the location information of 85 million users of NTT DOCOMO (as of March 2022)[25], MSS provides the population estimate at 500×500-meter mesh at an hourly level across Japan.[26] While physical mobility data has received significant attention in the social sciences since the onset of the COVID-19 pandemic (e.g., Google's COVID-19 Community Mobility Reports), such data are not yet widely used to examine avoidance behaviors or environmental stressors (see Burk et al. 2022).[27]

Our dataset on mobility measures is constructed as follows. First, for each municipality, we choose a 500×500-meter mesh with the largest number of establishments in the customer service industry (e.g., accommodation, restaurants, and entertainment) based on information obtained from the 2016 Economic Census (MIC 2019).[28] We choose the service industry to

[25] This is out of a 127 million individuals, being the total population of Japan.

[26] See Terada et al. (2013) for detailed procedures for constructing population estimates. There are two types of geolocation data in Japan: the first data comes 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. The most attractive feature of this data is that since it essentially follows each individual over time (but only in very recent years), researchers can identify "home" locations as the most frequent locations of geographically contiguous stays (Miyauchi et al. 2021) and measure whether the individual leaves their home. The drawback is that the sample is limited to individuals who gave permission to share location information, causing selection issues to the users of the particular application as well as those who gave permission, and also resulting in a small sample size (545,000 users as of 2019). On the other hand, the second data like ours, based on information transmission from each mobile terminal (of 78 million users in our case) to base stations, is more nationally representative with wide spatial coverage of the entire country, while it only provides the hourly estimated population in a given area. Since the main 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 of time, we chose the latter dataset for analysis in this study. Due to its representativeness and long-time span of the sample, this dataset has been widely used, especially in measuring people's mobility during the COVID-19 pandemic (e.g., Kondo 2021; Kuroda et al. 2022).

[27] As in the other studies on physical movement, we cannot distinguish two possibilities for staying indoors: people may be extremely sick and have to stay home or they may display some form of avoidance.

[28] Due to budgetary reasons, our data consist of one mesh per municipality. However, we confirm that our mobility measure captures overall daytime outdoor activities adequately, using the 2019 data for which we have an outdoor population for all meshes. Indeed, our mobility measure from the representative mesh correlates as

capture bustling areas (e.g., business districts, shopping, and dining areas), which are more likely to represent the population engaging in outdoor activities. Second, we provide the list of the meshes to NTT DOCOMO, Inc, which returns the estimated population at each mesh for the period February 2014 to May 2019. Third, we collapse the estimated population at the unit level by taking the average of all municipalities in the unit. We use the estimated population at 2 pm, as the daily population in commercial areas tends to peak around 2 pm (Seike et al. 2015).[29] We treat this measure as a proxy for engaging in outdoor activities ("outdoor population," hereafter) to examine avoidance behaviors.

Before examining the relationship between pollen load and mobility measures, we attempt to verify that curtailing outdoor activities is indeed effective in reducing the risk of accidents. To do so, we simply regress the number of accidents (our main outcome) on our mobility measure with the same sets of FEs and controls as Equation [1] (excluding a logged number of pollen counts). Table E1 shows that outdoor population is highly positively correlated with the number of accidents that occur, reassuring us that simply reducing outdoor activities can be a meaningful means to mitigate the risk of accidents (including traffic accidents that apparently occur outside), that is, $\left(\frac{\partial Accidents}{\partial Avoid} < 0\right)$.[30]

The magnitude of avoidance behaviors—. Figure 6 displays the binscatter plots of the relationship between the logged pollen counts and the logged outdoor population. Panel A shows no clear relationship between pollen counts and daytime outdoor population on average. Since most people should have more discretion to stay indoors on weekends than on weekdays, Panel B plots the same relationship for weekends only. Here, we find some negative relationships, suggesting that individuals seem to engage in some avoidance behaviors over the weekends.[31] However, as discussed below, the magnitude of avoidance is quite small.

Table 4 reports the estimate from Equation [1], where the outcome is logged number of outdoor populations. Columns (1) and (2) show that the estimates are negligible and far from statistically significant for all days and weekdays. Column (3) for weekends shows the

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high as 0.889 with the summary measure that uses the average of all the meshes with at least one establishment in the service industry.

[29] We also examine alternative methods of constructing outdoor mobility measures, specifically, the difference between daytime (2pm) and nighttime (4am) populations and the ratio of daytime to nighttime populations. The results are qualitatively similar (not shown) mainly due to the fact that the nighttime population is relatively stable over time, and thus it does not provide much additional information after controlling unit FE.

[30] Similarly, Barnes (2021) shows that mobility reduction due to the COVID-19 lockdown is associated with the decline in traffic accidents, using Google Community Mobility Reports in Louisiana.

[31] See Appendix Figure E1 for dose responses of avoidance behaviors for weekends only where logged daily pollen in Equation [1] is replaced by the dummies for each decile of daily pollen in levels.

elasticity of the outdoor populations with respect to pollen counts is as small as –0.0021 (p-value<0.01), implying that a 1% increase in pollen concentration leads to only a 0.0021% reduction in the number of outdoor populations. Table 4 also reports the estimates on four indicators for rainfall (base: no rainfall) for comparison. The outdoor population decreases as rain intensity increases, reassuring us that our mobility measure adequately captures individuals' decision-making process in relation to engaging in outdoor activities.[32] For example, the estimates from Column (3) indicate that rainfall between 1mm and 2mm reduces the outdoor population by 9.9 times more than a 1% increase in the pollen count.

For completeness, we quantify the contribution of avoidance behavior by comparing the estimates of Equation [1] with and without controlling for avoidance behaviors proxied by the logged number of outdoor populations. This result should be interpreted with considerable caution as the number of outdoor population is obviously endogenous or potentially "bad" controls (Aguilar-Gomez et al. 2022). Nonetheless, the estimate of the effect of pollen on accidents in Column (2) of Table 5 with avoidance control is almost identical to the one in Column (1) without such control (0.2163 vs. 0.2159), which is consistent with the limited avoidance behaviors documented so far. Table E3 repeats this exercise separately for weekdays and weekends, but even for weekends, the estimates of the effect of pollen on accidents increase only by 0.04 (from 0.269 to 0.273, or about 1.4%) by controlling avoidance behaviors, implying that "behavioral" and "biological" effects are similar each other at least in our setting.

Policy implications—. The behavioral responses we are able to measure show very little change to elevated pollen levels.[33] However, it is unlikely that this low response is driven by the sheer lack of awareness by pollen sufferers. If we assume the behavioral response term $\frac{\partial Avoid}{\partial Pollen}$ in Equation [2], which seems close to zero, can be further decomposed by adding an information channel as follows:

$$\frac{\partial Avoid}{\partial Pollen} = \underbrace{\frac{\partial Avoid}{\partial Information}}_{\text{salience of information}} \underbrace{\frac{\partial Information}{\partial Pollen}}_{\text{availability of information}}, [3]$$

Since the left-hand side (LHS) variable is nearly zero, and the second component of the RHS

[32] See Table E2 for the estimates of other weather covariates with expected signs: while the outdoor population increases as temperature rises, it decreases as the average wind speed and duration of darkness increases.
[33] Apparently, we only capture one type of avoidance behavior—refraining from going out to busy areas. There are other potentially cost-effective methods, such as wearing particulate-filtering masks and glasses and avoiding wearing the type of clothes that easily attract pollen (e.g., woolen coats).

variable—“availability of information”—seems quite positive (as evident from Google Trend and Twitter analysis), the first component of RHS— “salience of information”—should be close to zero in our case (“this is irrelevant to me”). This distinction is important for policy considerations since if there is a problem with access to information, we would suggest that the government should attempt to increase the dissemination of pollen information more widely (Barwick et al. 2020; Jha and Nauze 2022). On the other hand, if access to information is of a sufficient level, but awareness is lacking, we would have to propose more effective ways to raise awareness of the risks (“salience”) and encourage further behavioral change. For example, the public information campaigns such as “pollen alert”—that encourage decreasing outdoor activities or that recommend using public transportation on high pollen days due to the heightened risk—can be a possibly low-cost and effective tool to reduce pollen-induced accidents.[34] In fact, a few studies demonstrate that alerts of smog and ozone successfully induce people to take precautionary actions to reduce exposure (e.g., Anderson et al. 2022; Neidell 2009).

Unlike “ex-post” government interventions like pollen alerts, the “ex-ante” interventions, such as trimming pollen-emitting plants and replanting newly invented less pollen-emitting trees (such as in the case of the Japanese cedar) to remove the source of pollen “production” could be more cost-effective in the long-run. However, such a process may take time, and thus ex-post intervention, like the pollen alert system, can be a temporary remedy.

5.6. Medium-term adaptation

While we find limited evidence of *short-term* avoidance behaviors, longer-term adaptation (either technological, behavioral, or biological) may also take time. Recent medications for seasonal allergies cause less drowsiness and reduce the risk of unsafe driving. See Table A1 for the list of medications for seasonal allergies released during the period 1994 to 2017 in Japan. This table indicates that more recent medications do not tend to have any specific mention of the medication’s effect on driving ability, unlike past medications that mention either “Driving not allowed” or “Careful driving required.”[35] Individuals may also

[34] To the extent that the lack of avoidance behavior reflects people’s revealed preferences that already incorporate the potential risk, raising the awareness of risk may not have as meaningful an impact as we might expect.

[35] A few studies document higher sales of over-the-counter medications for pollen allergies and face masks on days with high pollen counts (e.g., Ito et al. 2015; Kuroda 2022; Sheffield et al. 2011). Our analysis of Google Trend and Twitter data for medication-related keywords supports these findings.

engage in defensive spending (e.g., buying air purifiers) over a longer time span. Furthermore, unlike short-run physiological acclimatization, *behavioral* acclimatization may require more time to take effect (Graff Zivin and Neidell 2014).

We examine the effect of medium-term adaptations to pollen exposure in Panels E and F of Figure 5. First, Panel E shows that the effect of pollen in May—the last month of the Spring pollen season in most parts of Japan—is no smaller than the effects for other early months, such as February and March. This result contrasts with the short-run acclimatization to heat exposure in Graff Zivin and Neidell (2014), documenting that the responses in time allocation to heat are smaller in August than in June. Second, in terms of *longer*-term adaptive possibilities, we might expect the pollen sensitivity of accidents to decrease over time. We empirically test this by dividing the 12-year sample period (2008–2019) into three intervals of four years each. Panel F of Figure 5 shows that while pollen-accident sensitivity becomes marginally smaller in the last period than in the earlier periods, the magnitude of the decline is slight, and none of the estimates in the three intervals are statistically distinguishable from each other.[36]

Finally, we divide 705 units into quantiles by the mean of pollen counts during the period 2008 to 2019 to investigate whether people who live in high pollen regions, on average, experience smaller impacts of pollen concentrations than those who live in low pollen concentration regions through undertaking a series of longer-term adaptation. Figure C5 indicates that the estimates are reasonably similar across quantiles, again demonstrating limited longer-term adaptive potential. In the end, we fail to find compelling evidence of medium-term adaptation to the destructive impact of pollen exposure.

5.7. Projecting damages due to climate change

This section combines the estimates on the effect of pollen exposure on accidents documented thus far with projections of future climate, as well as the relationship between the temperature and pollen counts obtained in Figure 1, to measure the magnitude of expected changes in the number of pollen-induced accidents from a climate change perspective.[37]

[36] Figure C4 plots the estimates of every single year (instead of 4-year intervals) *relative to* the baseline year of 2008 to be completely flexible. Again, we do not find an obvious declining pattern over the 12-year period.

[37] We acknowledge that we make a strong assumption that the marginal treatment effect of an unanticipated "weather" shock documented so far is identical to the marginal effect of an anticipated "climate" shift. Past studies have done similar exercises of projecting the impact of these gradual changes on income (Deryugina and Hsiang 2014), crime (Ranson 2014), mortality (Deschênes and Greenstone 2011), amenity values (Baylis 2020), and other outcomes.

Table 6 summarizes the projected damages based on the "business as usual" scenario (RCP 8.5), which predicts that the summer temperature in Japan will increase by 4.1℃ in the years 2076 to 2095 (MEXT and JMA 2020). We calculate the number of additional pollen-induced accidents associated with this temperature change as follows: Based on the relationship between the summer temperature and pollen counts (Panel A of Figure 1), this increase in temperature could lead to additional daily pollen counts of 686 (= 167.4×4.1) grains/m^3, which would correspond 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 4 for each severity level by 0.529, and then by 120 (days that make up a typical pollen season), and then further by 127.4 (relating to the population figure) to calculate the additional annual accidents as is reported in Row (1). Row (1) indicates that a 4.1℃ increase in the average summer season temperature is expected to increase the pollen-induced death/fatal, serious, moderate, and light accidents by 30, 216, 541, and 1036, respectively, bringing the total number of additional annual accidents to 1,823.

We then convert these 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 is reported in Row (2). We determine the prospective additional cost to be \$3.2 million for fatal accidents (those resulting in death), \$365,000 for accidents resulting in serious injuries, and \$38,000 for those resulting in both moderate and light injuries.[38] Row (3) demonstrates that pollen-induced accidents resulting in death or fatal injuries, serious, moderate, and light injuries translate into actual monetary costs of \$96.3 million, \$79.1 million, \$20.6 million, and \$39.6 million, respectively. This equates to a total annual social cost of \$236 million, which can be seen in Row (4). Interestingly, this figure far exceeds the budget for the Japanese Forestry Agency's pollen reduction program, which is currently \$1.1 million (Forest Agency 2021).[39]

We note that it is likely that our simple damage projection calculation has likely yielded a conservative estimate since (i) we have not taken into account any extension of the pollen season due to the increasingly hotter summer seasons, (ii) we only considered approximately four months of high pollen season (see Figure A2 of the pollen calendar), (iii) we have been unable to take into account the accidents that occur at both sides of the severity distribution

[38] For simplicity, an exchange rate of 1.5 \$/£ is used. Unfortunately, to our knowledge, there are no appropriate estimates of accident costs at each severity level in Japan.

[39] Panel B of Table 5, using the number of days where the temperature increased above 30℃ in the previous year (Panel B of Figure 1), gives roughly 40% larger estimates of social cost than using the maximum temperature in Panel A of Table 5.

spectrum (i.e., minor cases that do not require ambulance transportation to hospitals as well as immediate deaths), and (iv) we made use of the relatively conservative value of a statistical life (Bünnings and Schiele 2021) rather than more commonly utilized value.[40]

6. Conclusion

We provide, to our knowledge, the first assessment of the impact of pollen exposure on the incidence of accidents using Japanese archived ambulance records for the period 2008 to 2019. We find that exposure to elevated pollen levels increases the occurrence of all types of accidents. Our results are consistent with well-established, clinically-based studies that have documented the adverse cognitive effects of pollen exposure, the long-term implications of which have not previously been assessed in the real-world, except for children's academic performance. In addition, as we find the effects of pollen exposure to be broadly uniform across a range of observed demographics, locations, and calendar months, and limited evidence of changes in the treatment effects over time, the underlying mechanism linking pollen exposure to accidents may be generalizable across different contexts.

Our analysis of internet search activities and social media posts for pollen-related topics suggests that individuals seem to have a good awareness of daily pollen levels. However, information indicating limited avoidance behaviors gathered from geolocation data implies that they may underestimate the risks of pollen exposure. Thus, the status quo that relies on individuals' self-protection to mitigate pollen exposure may only have limited benefits. Governmental efforts to raise awareness of the risks of exposure and promote widespread behavioral change might be necessary.

Finally, it is imperative to reiterate that the estimated social costs we establish might only reflect the tip of the iceberg of the potentially extensive social cost associated with increasing pollen counts. While we remain agnostic about the underlying mechanisms, to the extent that exposure to pollen impairs cognitive function, any daily human activity that requires normal cognitive performance and decision-making abilities can be similarly affected. It is vital to quantify the potential damage as this is an avenue that can lead to a better understanding of the full costs of pollen concentration.

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

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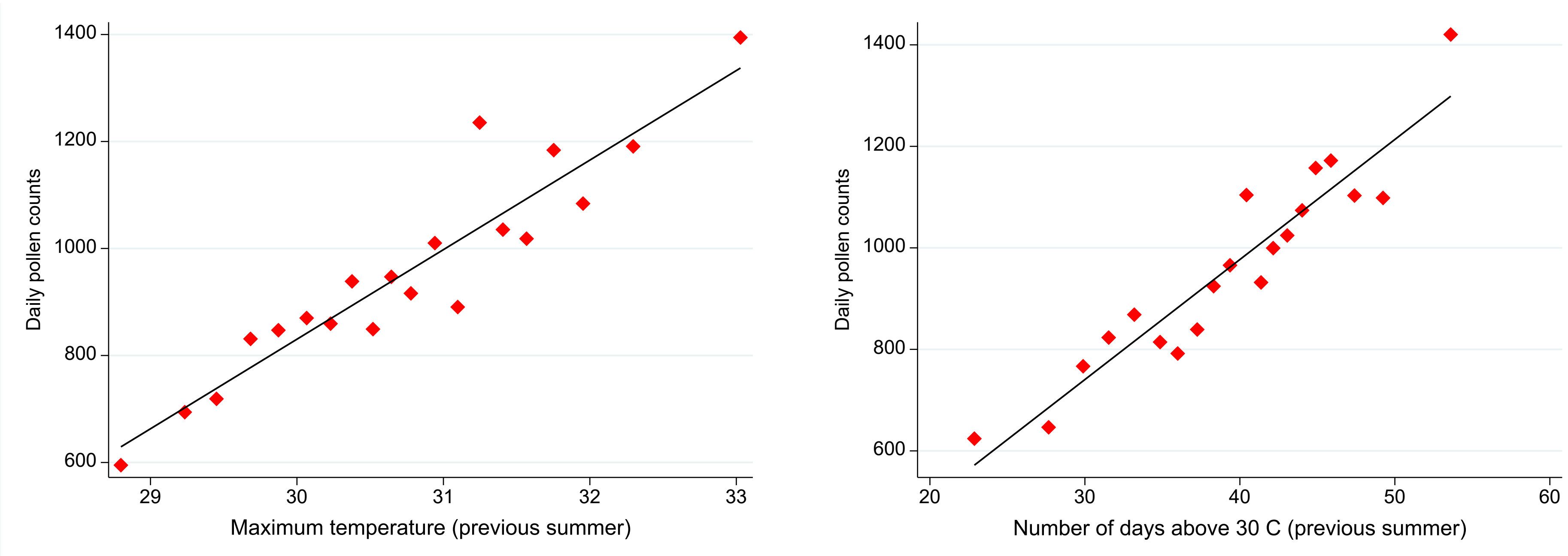
Figure 1—Pollen counts and heat in the previous summer

A. Maximum temperature in the previous year

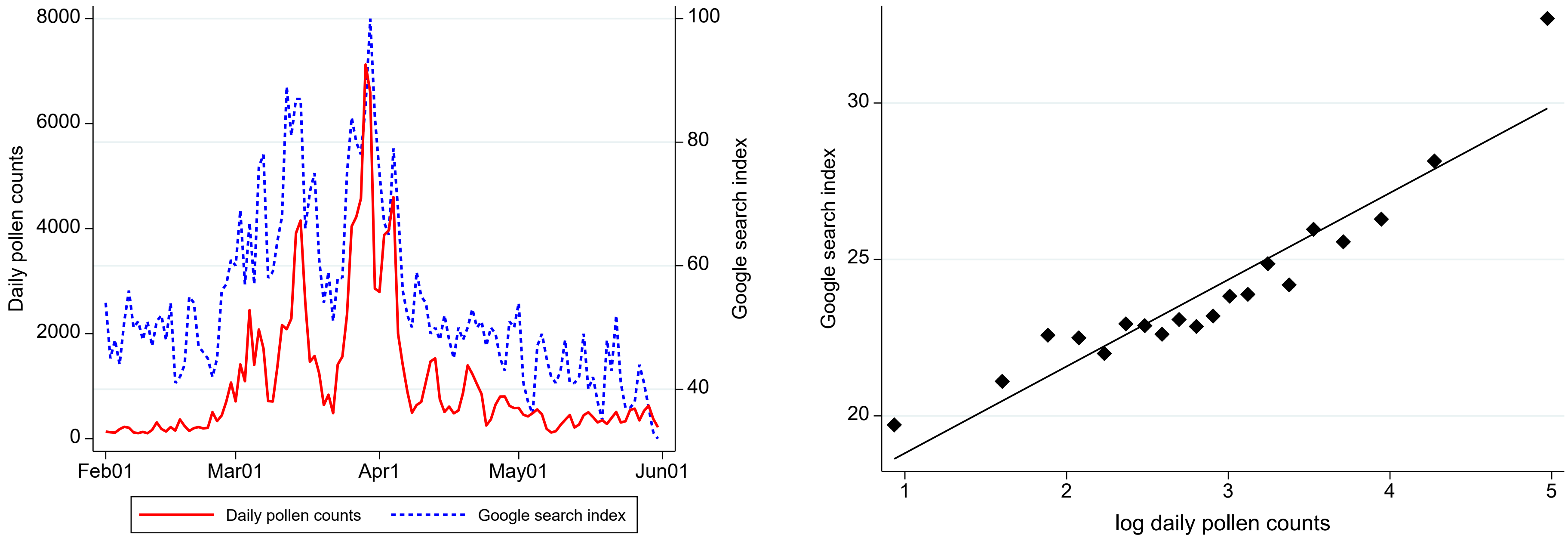
B. Number of days above 30°C in the previous year



Notes: The graphs display the binscatter plots of the relationship between average (24-hour cumulative) daily pollen counts (grains/m^3) for the period February to May and the average maximum temperature (in °C) in Panel A and the number of days the temperature exceed 30°C in Panel B in July and August in the *previous* summer season after controlling for pollen monitoring station fixed effect (FE). The sample consists of station-year (N = 1440) from all the pollen monitoring stations (N=120) during the period 2008 to 2019 (12 years). The slope in Panel A is 167.4 (t-stats= 11.16), indicating that a one degree increase in the maximum temperature in the previous summer season increases the daily pollen counts by 167.4 grains/m^3. Similarly, the slope in Panel B is 23.7 (t-stats= 11.18), indicating that ten additional hot days above 30°C in the previous summer season increases the daily pollen counts by 237 grains/m^3. The mean and median of daily pollen counts from February to May 2008 to 2019 at 120 monitoring stations are 955.6 and 712.5 grains/m^3, respectively.

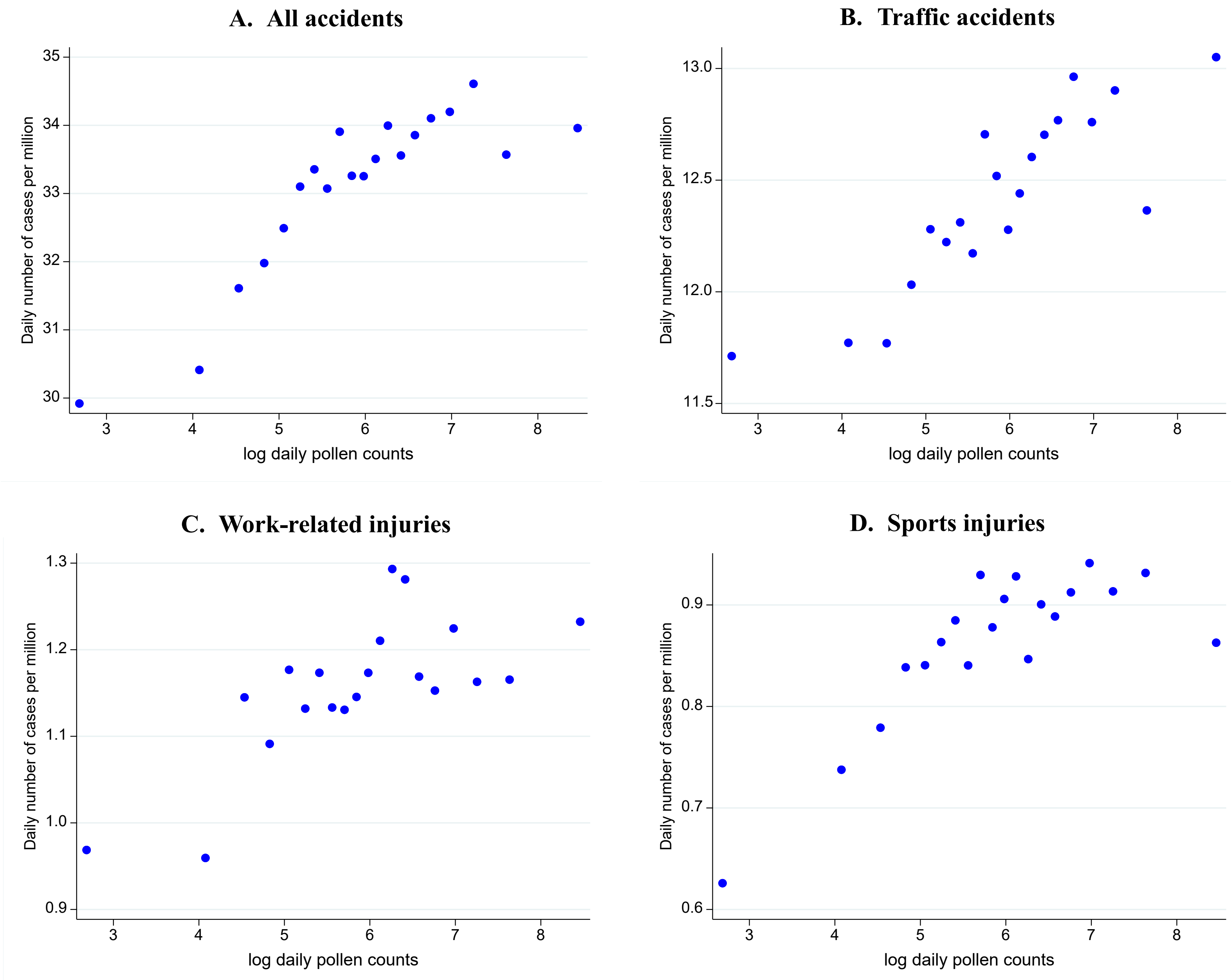
Figure 2—Pollen and symptom-related Google search index

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

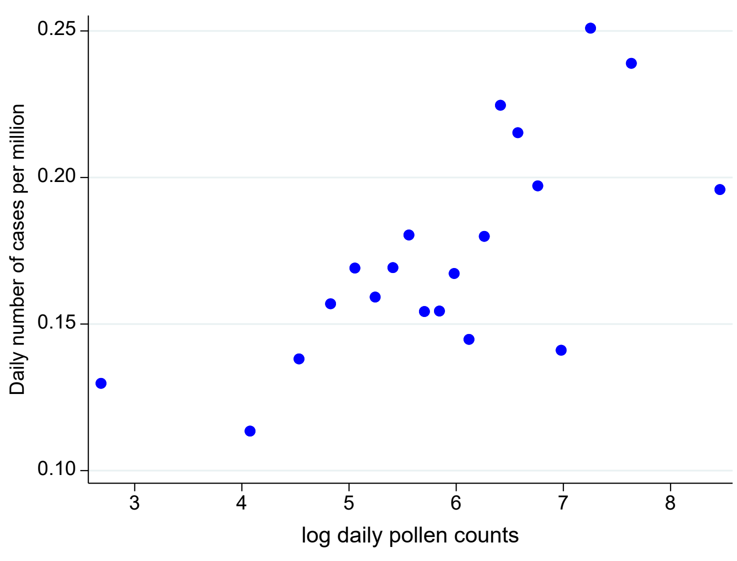


Notes: Panel A shows the time series patterns of the average daily pollen counts (grains/m^3) and Google search index for symptom-related keywords in 2018 at the country level. The symptom-related keywords are "runny nose," "nasal congestion," "sneeze," and "itchy eyes." June is omitted as only four stations in Hokkaido (the northernmost island of Japan) are still operating in June. Panel B displays the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and Google search index for the same keywords, after controlling for the month-by-year, month-by-prefecture, and day-of-week FE. See Figures B1 and B2 for similar plots for pollen allergy-related and medication-related keywords, which show similar patterns.

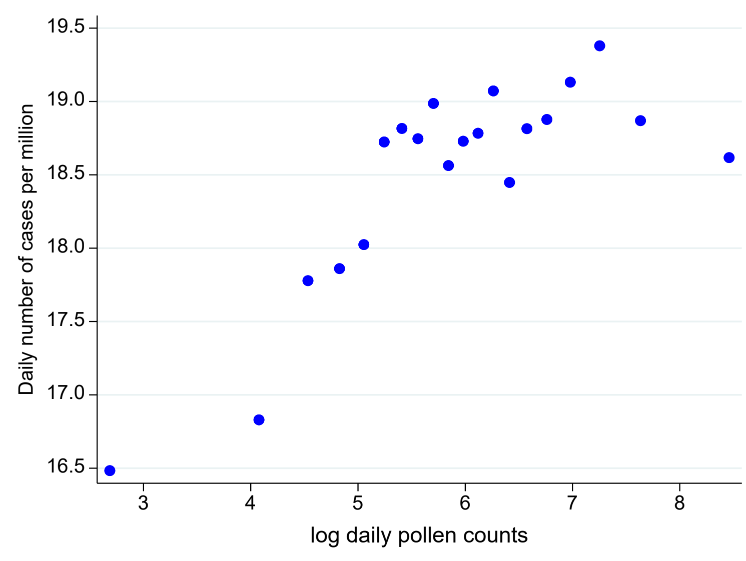
Figure 3—Daily pollen counts and the number of accidents



E. Accidents involving fire

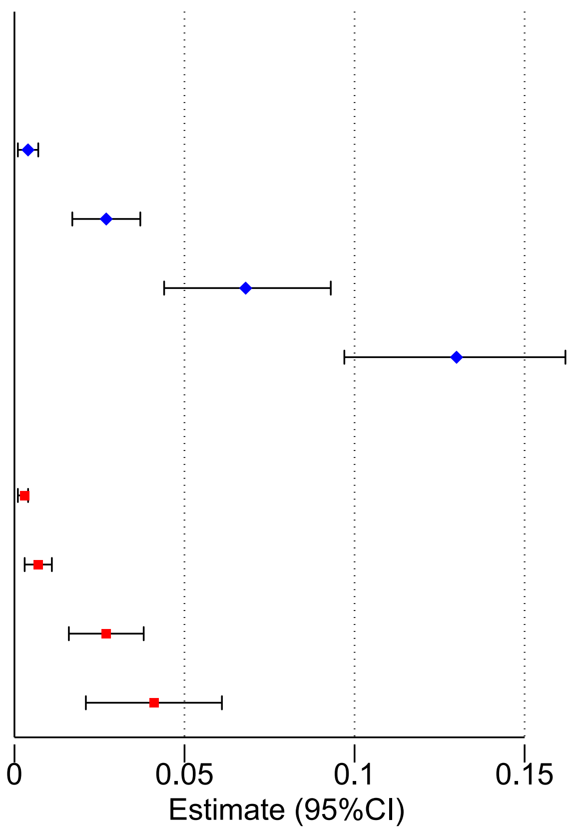


F. Other accidents



Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N = 970,309). There are 705 units in total. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the number of daily cases per million people for all accidents in Panel A and for each type of accident in Panels B to F: traffic accidents (Panel B), work-related injuries (Panel C), sports injuries (Panel D), accidents involving fire (Panel E), and other accidents (Panel F) after controlling for the unit, month-by-year, month-by-prefecture, and day-of-week FEs. The shares of traffic accidents (Panel B), work-related injuries (Panel C), sports injuries (Panel D), fire accidents (Panel E), and other accidents (Panel F) are 37.6%, 3.5%, 2.6%, 0.5%, and 55.8%, respectively. The population in each unit is used as weights.

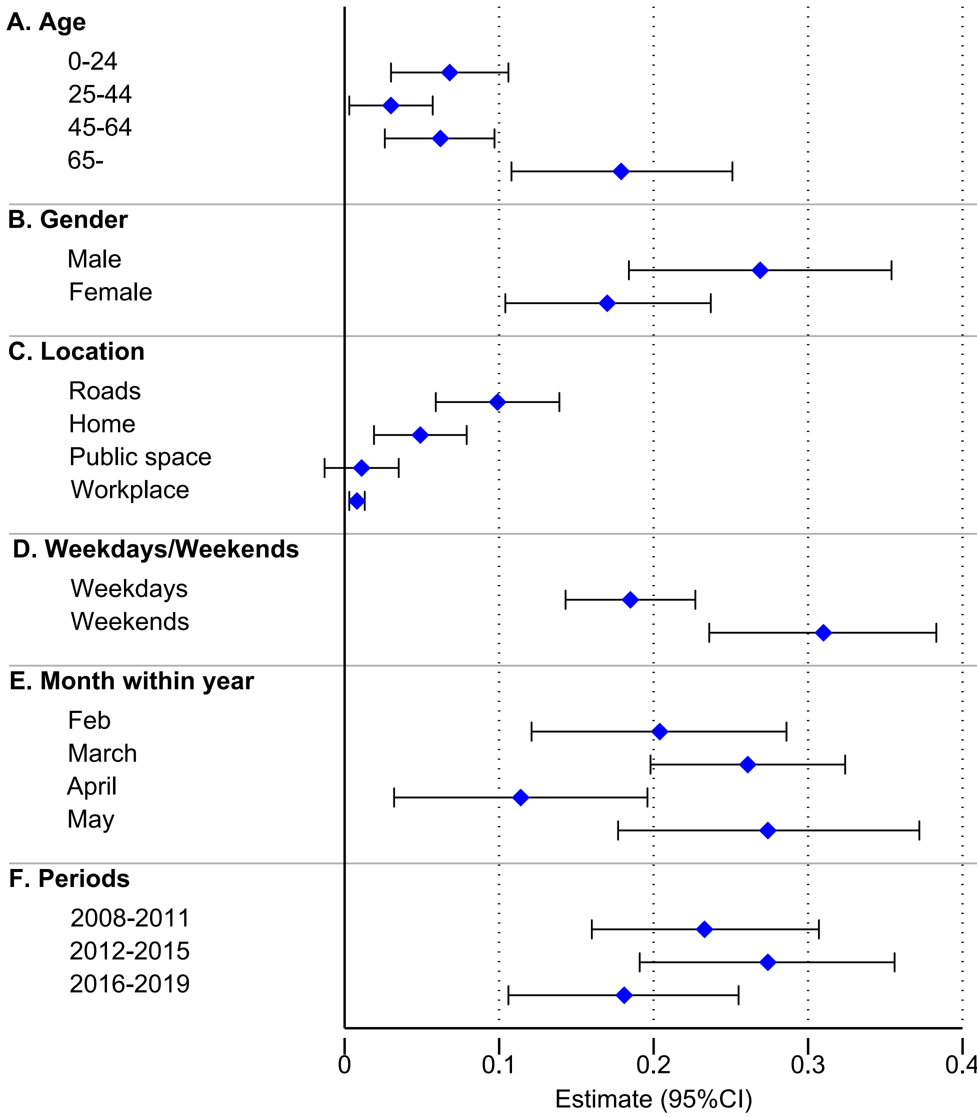
Figure 4—Treatment effects by severity



	Estimate (95%CI)	Mean	Rel. to mean
A. All accidents			
Death/Fatal	0.004 (0.001, 0.007)	0.30	1.27 %
Serious	0.027 (0.017, 0.037)	2.05	1.31 %
Moderate	0.068 (0.044, 0.093)	9.05	0.75 %
Light	0.130 (0.097, 0.162)	21.58	0.60 %
B. Traffic accidents			
Death/Fatal	0.003 (0.001, 0.004)	0.08	3.32 %
Serious	0.007 (0.003, 0.011)	0.49	1.44 %
Moderate	0.027 (0.016, 0.038)	2.29	1.19 %
Light	0.041 (0.021, 0.061)	9.53	0.43 %

Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95% confidence interval of treatment effects of logged daily pollen count from Equation [1]. The standard errors are clustered at pollen monitoring station levels. The dependent variable is the number of daily cases per million people for each severity level. The severity is based on the doctor's judgment at the time of hospital admission. "Serious" accidents are defined as such when the level of injuries requires more than three weeks of hospitalization and treatment; "moderate" requires hospital admission, but hospitalization of less than three weeks, and "light" does not require hospital admission. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. The mean reported second to the far right is the number of daily cases per million people. The relative to the mean reported on the far right is the estimate divided by the mean.

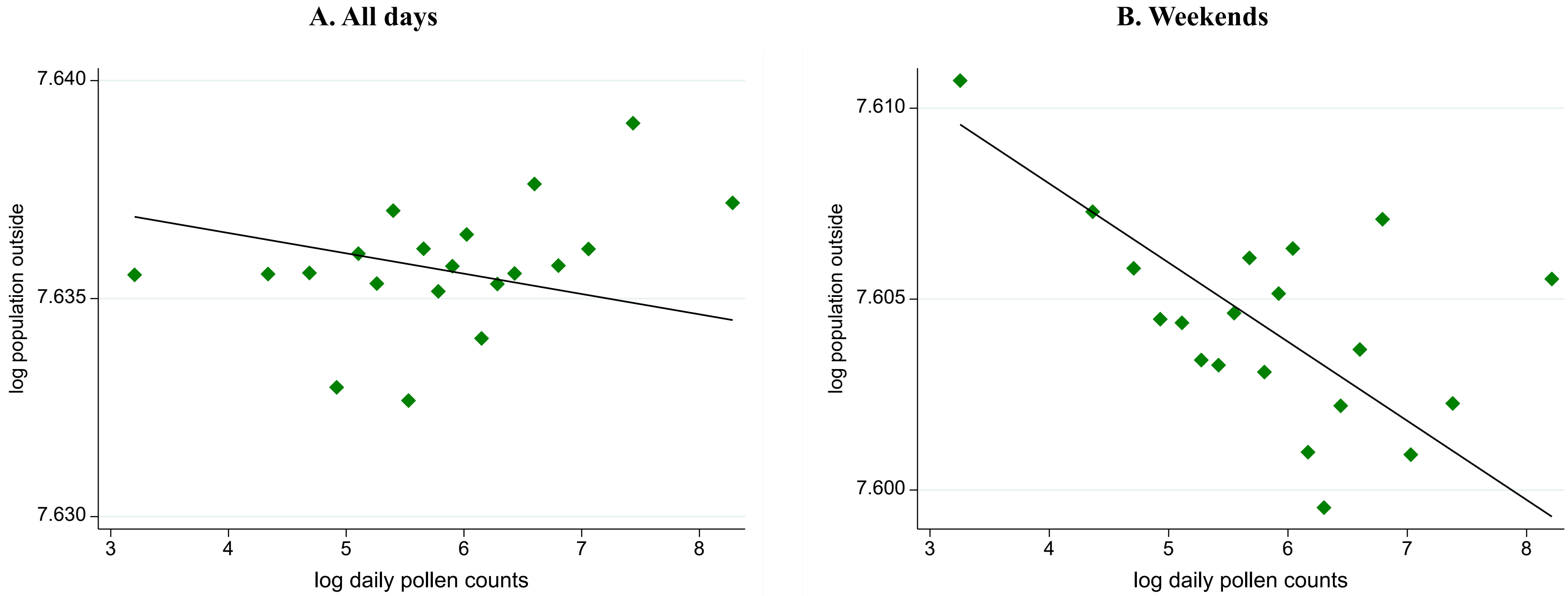
Figure 5—Other heterogeneous treatment effects (All accidents)



	Estimate (95%CI)	Mean	Rel. to mean
A. Age			
0-24	0.068 (0.030, 0.106)	6.34	1.07 %
25-44	0.030 (0.003, 0.057)	4.61	0.65 %
45-64	0.062 (0.026, 0.097)	5.81	1.06 %
65-	0.179 (0.108, 0.251)	14.09	1.27 %
B. Gender			
Male	0.269 (0.184, 0.354)	15.88	1.69 %
Female	0.170 (0.104, 0.237)	13.91	1.23 %
C. Location			
Roads	0.099 (0.059, 0.139)	8.73	1.13 %
Home	0.049 (0.019, 0.079)	6.61	0.74 %
Public space	0.011 (-0.013, 0.035)	3.51	0.31 %
Workplace	0.008 (0.003, 0.013)	0.58	1.39 %
D. Weekdays/Weekends			
Weekdays	0.185 (0.143, 0.227)	32.10	0.58 %
Weekends	0.310 (0.236, 0.383)	35.39	0.87 %
E. Month within year			
Feb	0.204 (0.121, 0.286)	33.15	0.61 %
March	0.261 (0.198, 0.324)	32.88	0.79 %
April	0.114 (0.032, 0.196)	33.29	0.34 %
May	0.274 (0.177, 0.372)	33.09	0.83 %
F. Periods			
2008-2011	0.233 (0.160, 0.307)	31.60	0.74 %
2012-2015	0.274 (0.191, 0.356)	33.12	0.83 %
2016-2019	0.181 (0.106, 0.255)	34.30	0.53 %

Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95% confidence interval of heterogeneous treatment effects of logged daily pollen count from Equation [1]. The standard errors are clustered at pollen monitoring station levels. The dependent variable is the number of daily cases of accidents per million people using all accident data. The mean reported second to the far right is the number of daily cases per million people. The relative to the mean reported on the far right is the estimate divided by the mean.

Figure 6—Pollen and avoidance behaviors



Notes: The sample is derived from cell-phone location data for the period 2014 to 2019, and the level of observation is a unit per day (N =478,853 for Panel A and 135,399 for Panel B). There are 705 units in total. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the logged daily number of people outdoors at 2 pm for all days in Panel A and only for weekends in Panel B, controlling for the month-by-year, month-by-prefecture, and day-of-week FEs, weather covariates (precipitation, temperature, wind speed), darkness, and logged population. The population in each unit is used as weights.

Table 1—Descriptive 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: Accidents involving fire	*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: Serious	*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: Light	*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 count (grains/m^3)		970,309	984.3	2135.3	0	55,104
Log (Pollen count)		970,309	0.2	0.4	0	9.6
Precipitation (mm)		970,309	11.9	6.1	0	28
Average temperature (℃)		970,309	2.9	1.4	0	15.7
Average wind speed (m/s)		970,309	10.5	1.3	7	13
Darkness (hours)		852,948	2.2	2.2	0	521
SO_2 (ppb)		846,719	6.1	10.1	0	307
NO_2 (ppb)		846,659	15.1	9.6	0	88
CO (0.1ppm)		848,798	4.0	1.8	0	61
OX (ppb)		850,847	36.8	11.5	0	120
PM10 (μg/m^3)		850,577	20.0	11.1	0	299

Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day. There are 705 units in total. The population in each unit is used as weights. The share within the *category* should be summed up to 100%. The pollution data is available from 2009 onwards.

Table 2—Main results

	A. All accidents	B. By type				
		Traffic accidents	Work-related injuries	Sports injuries	Accidents involving fire	Other accidents
	(1)	(2)	(3)	(4)	(5)	(6)
log (pollen)	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
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-year FE	X	X	X	X	X	X
Month-prefecture FE	X	X	X	X	X	X

Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N = 970,309). There are 705 units in total. The dependent variable is the number of daily cases per million people for each accident type. The estimates from Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. In addition to the fixed effects in the table, we include weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10.

Table 3—Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Construction of pollen measures		Other			Expanding windows of outcome		
	Baseline	Weighted average of nearby three stations	Drop zero pollen observations	(1)+Add pollution	Units within 48 km from stations	Un-weighted	Add the following one day	Add the following two days	Collapse data at weekly
A. All accidents									
log (pollen)	0.231***	0.234***	0.249***	0.220***	0.229***	0.402***	0.236***	0.265***	0.213***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.020)	(0.066)	(0.037)	(0.052)	(0.036)
R-squared	0.46	0.46	0.46	0.47	0.48	0.33	0.62	0.71	0.85
N	970,309	970,309	962,255	814,578	872,227	970,309	961,901	953,522	147,066
B. Traffic accidents									
log (pollen)	0.079***	0.082***	0.090***	0.073***	0.078***	0.137***	0.086***	0.110***	0.124***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.037)	(0.019)	(0.027)	(0.020)
R-squared	0.24	0.24	0.24	0.24	0.26	0.12	0.38	0.48	0.70
N	970,309	970,309	962,255	814,578	872,227	970,309	961,901	953,522	147,066

Notes: The sample is derived from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day. There are 705 units in total. The estimates from variants of Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. Column (1) replicates the results from Table 2 (baseline) for ease of comparison. Column (2) uses the daily pollen counts constructed by the inversely weighted average of three nearby stations as the main regressor. Column (3) drops zero pollen counts (0.83%) and takes a log without adding 1. Column (4) adds air pollution covariates (SO_2, NO_2, CO, OX, PM10) for the period April 2009 to April 2019 when such data is available. Column (5) restricts the sample to the units within 48 km of monitoring stations. Column (6) is an unweighted ordinary least square (OLS). Columns (7) and (8) add the number of accidents on the following day and the number of accidents on the following two days to the outcome, respectively. Column (9) collapses the data at the weekly level. All specifications include unit, month-by-year, month-by-prefecture, and day-of-week FEs except for Column (9). Column (9) includes unit, year-by-prefecture, and week-by-unit FEs. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 4—Avoidance behaviors

	A. All	B. By type of day	
		Weekdays	Weekends
	(1)	(2)	(3)
log (pollen)	-0.0005	0.0000	-0.0021***
	(0.0006)	(0.0006)	(0.0007)
Rain (base: no rain)			
<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
Pref FE	X	X	X
Day-of-week FE	X	X	X
Month-year FE	X	X	X
Month-prefecture FE	X	X	X

Notes: The sample is derived from cell-phone location data for the period February to March for the years 2014 to 2019, and the level of observation is a unit per day. There are 705 units in total. The estimates from Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. The outcome is the logged daily number of outdoor population at 2 pm. In addition to the fixed effects and weather covariates in the table, we include average wind speed, darkness, and logged population. Estimates are weighted by the population in each unit. See Appendix Table E2 for the estimates of all other weather covariates. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 5—Controlling avoidance behaviors

	A. All accidents		B. Traffic accidents	
	(1)	(2)	(3)	(4)
log (pollen)	0.2159***	0.2163***	0.1038***	0.1040***
	(0.0306)	(0.0307)	(0.0186)	(0.0186)
log (number of outdoor population)		0.9663**		0.4867**
		(0.4190)		(0.2244)
R-squared	0.49	0.49	0.24	0.24
N	478,853	478,853	478,853	478,853
Unit FE	X	X	X	X
Day-of-week FE	X	X	X	X
Month-year FE	X	X	X	X
Month-prefecture FE	X	X	X	X

Notes: The sample derives from ambulance records for the period 2014 to 2019 that are matched to "Mobile Spatial Statistics" data provided by NTT DOCOMO, Inc at the unit-day level (N= 478,853). There are 705 units in total. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. The estimates from a variant of Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. The dependent variable is the number of daily accidents per million people. Columns (2) and (4) add the logged number of outdoor population at 2pm to Columns (1) and (3), respectively. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

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

		A. Maximum temperature (+4.1℃)				B. Number of days above 30°C (+48.6 days)			
	Severity level	*Death/fatal*	*Serious*	*Moderate*	*Light*	*Death/fatal*	*Serious*	*Moderate*	*Light*
(1)	Increases 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 (USD)	*3,196,383*	*365,453*	*38,177*	*38,177*	*3,196,383*	*365,453*	*38,177*	*38,177*
(3)	Social cost per year (million USD)	96.34	79.06	20.63	39.57	141.11	115.79	30.22	57.95
(4)	Total social cost per year (million USD)	235.6				345.1			

Notes: Panel A uses the relationship between pollen counts and maximum temperature (Panel A of Figure 1), and Panel B uses the relationship between pollen counts and the number of days the temperature is above 30°C (Panel B of Figure 1). The total social cost per year in Row (4) for Panel A is calculated as follows: The increase in average temperature by 4.1°C from the "business as usual" scenario (RCP 8.5) leads to an increase in the daily pollen counts by 686.3 (=167.4 × 4.1), where 167.4 comes from Panel A of Figure 1. This leads to 0.529 increases in logged pollen counts from the mean (=*log*(984.34 +686.3)-*log*(984.34)). Row (1) is the product of each severity level estimate from Table 4 and 0.529, then by 120 days (Feb to May) of typical pollen seasons in Japan, and finally by 127.4, which is the average population (in millions) in Japan during the period 2008 to 2019. The figures in Row (2) are obtained from Bünnings and Schiele (2021) in the in the United Kingdom, and an exchange rate of 1.5 USD/£ is used. Row (3) is the product of Row (1) and Row (2). Row (4) is the sum of Row (3) for all severity levels. Similarly, for Panel B, the increase in the number of days where the temperature increases above 30°C by 48.6 days leads to an increase in the daily pollen counts by 1151.8 (=23.7 × 48.6), where 23.7 comes from Panel B of Figure 1. This leads to 0.775 increases in logged pollen counts (=*log*(984.34+1151.8)-*log*(984.34)). The calculations for Rows (3) and (4) are identical.

Online Appendix
(Not for Publication)

"Invisible Killer": Seasonal allergy and accidents

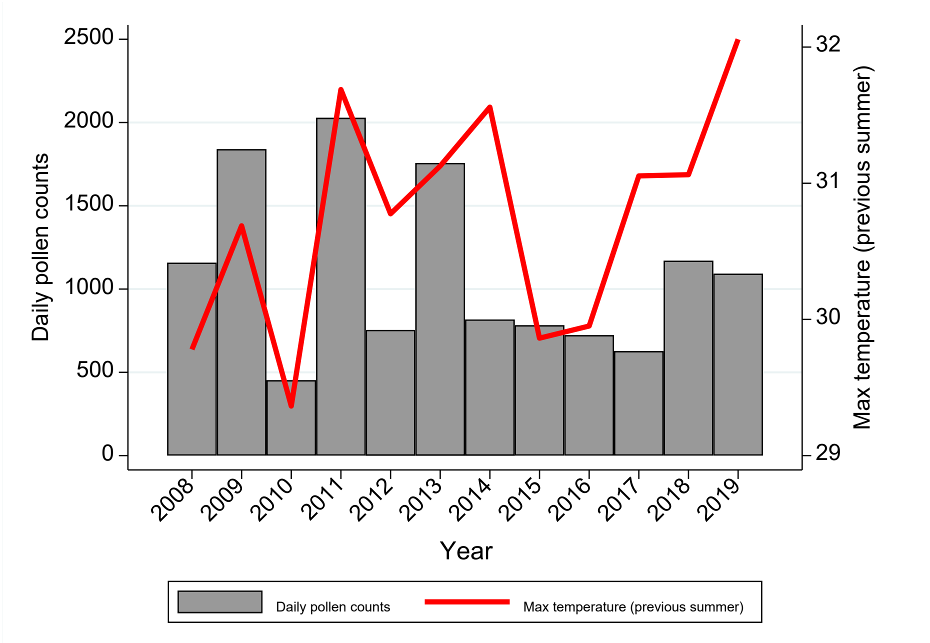
By Mika Akesaka and Hitoshi Shigeoka

Table of Contents

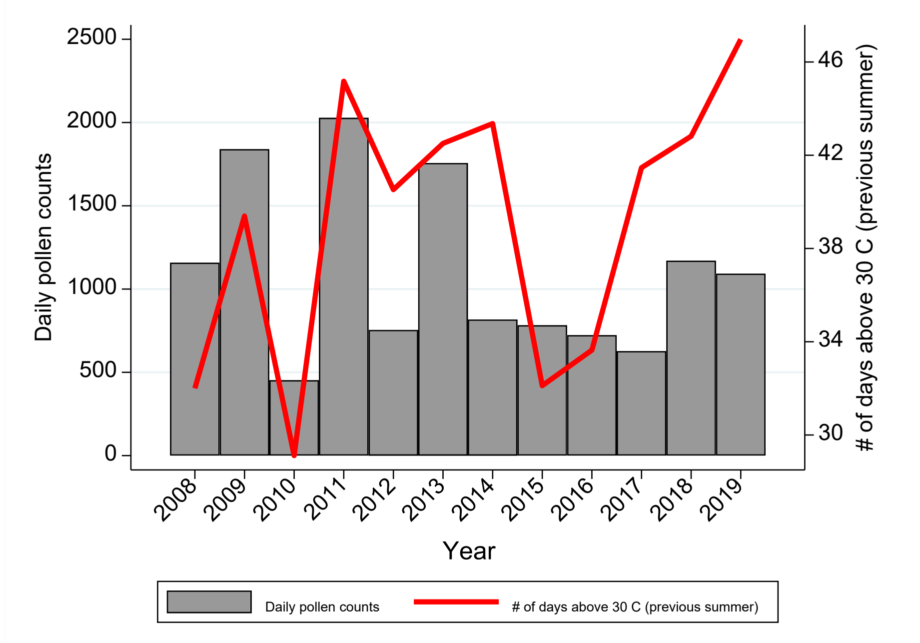
Appendix A: Additional Figures and Tables

Figure A1—Times series of pollen counts and maximum temperature

A. Maximum temperature in the previous year

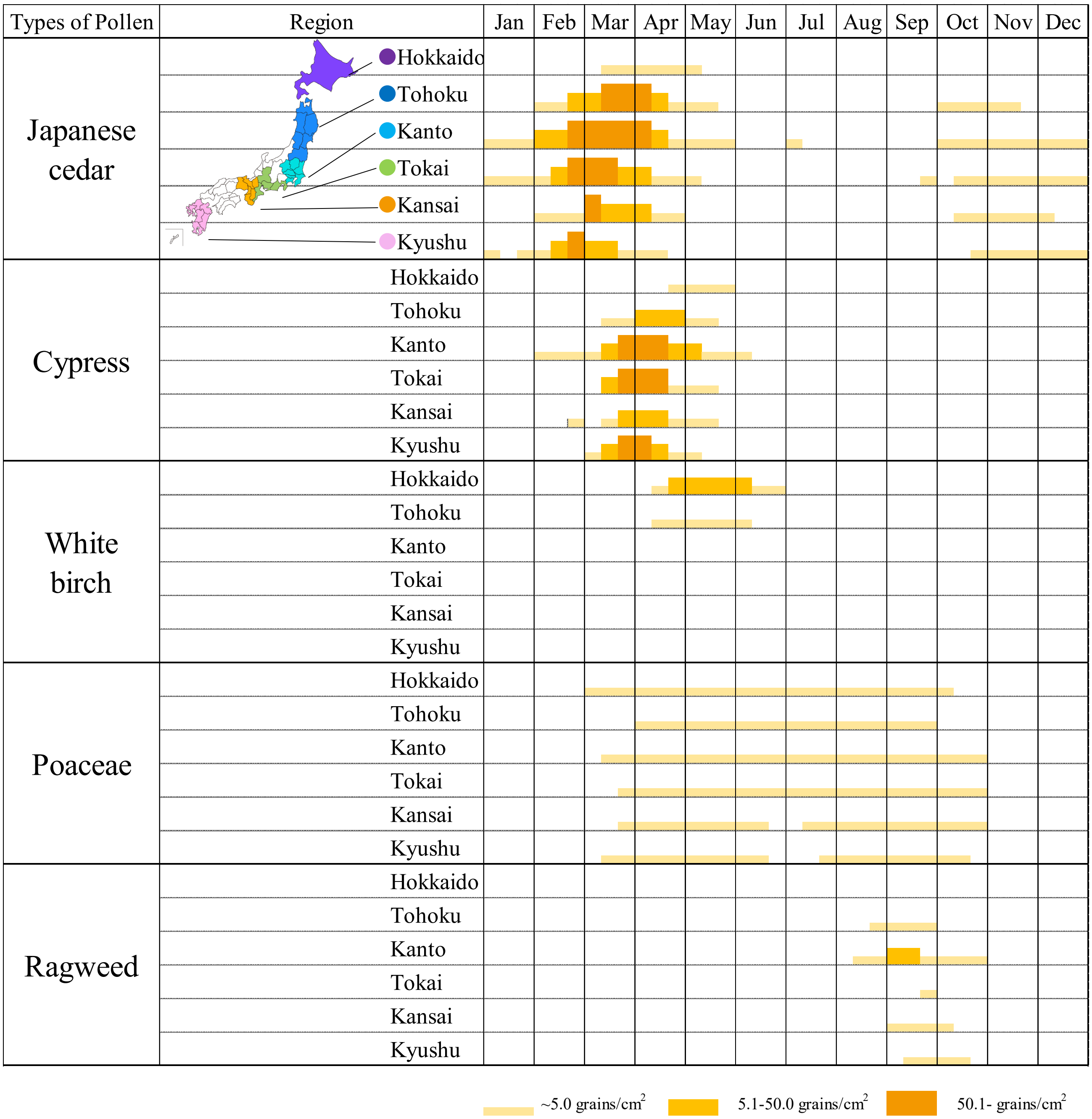


B. Number of days above 30 °C in the previous year



Notes: The figure shows the relationship between average daily pollen counts (grains/m^3) for the period February to May and, the average maximum temperature (in °C) in Panel A and the number of days the temperature rose above 30°C in Panel B during July and August in the *previous* summer season from 120 pollen monitoring stations during the period 2008 to 2019.

Figure A2—Calendar of pollen season in Japan



Notes: The figure shows the pollen dispersal season in Japan for five selected pollen types: Japanese cedar, cypress, white birch, poaceae, and ragweed for six regions in Japan (Hokkaido, Tohoku, Kanto, Tokai, Kansai, and Kyushu). Pollen Monitoring System called "Hanaok-san," operated by the Ministry of the Environment, monitors the hourly pollen of Japanese cedar and cypress from February to May, except for Hokkaido, which is covered from March to June. The height indicates the average amount of pollens.
Source: Kishikawa et al. (2020)

Figure A3—Real-time and forecasted pollen levels reported on TV

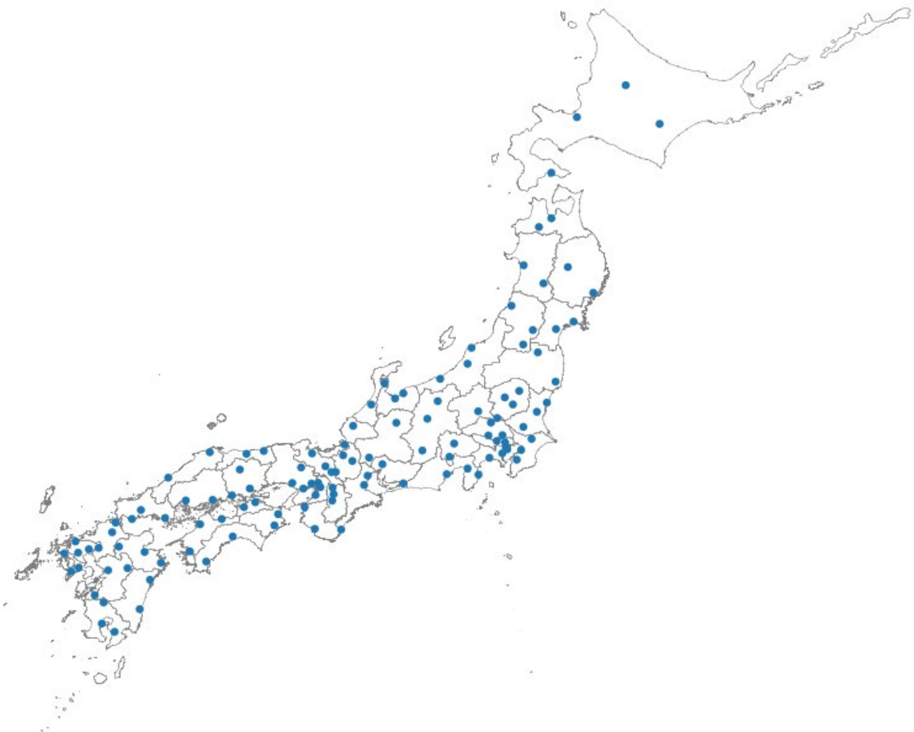
A. Today's forecast

B. This week's forecast

Notes: The figures show the pollen level reported on TV on a typical day during the pollen seasons in Japan. Panel A displays real-time pollen levels at various locations, and Panel B displays the forecast of this week's pollen level (for March 1 to March 6 as of February 28 in 2021) of differing magnitudes at various locations from the south to the north of Japan.

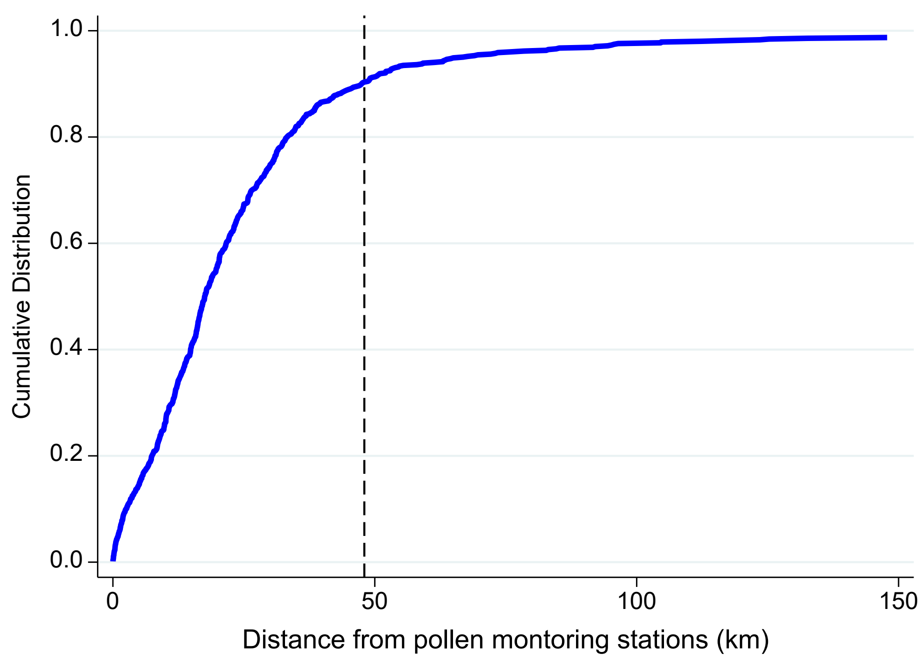
Sources: Japan Weather Association (2022)

Figure A4—Location of pollen stations



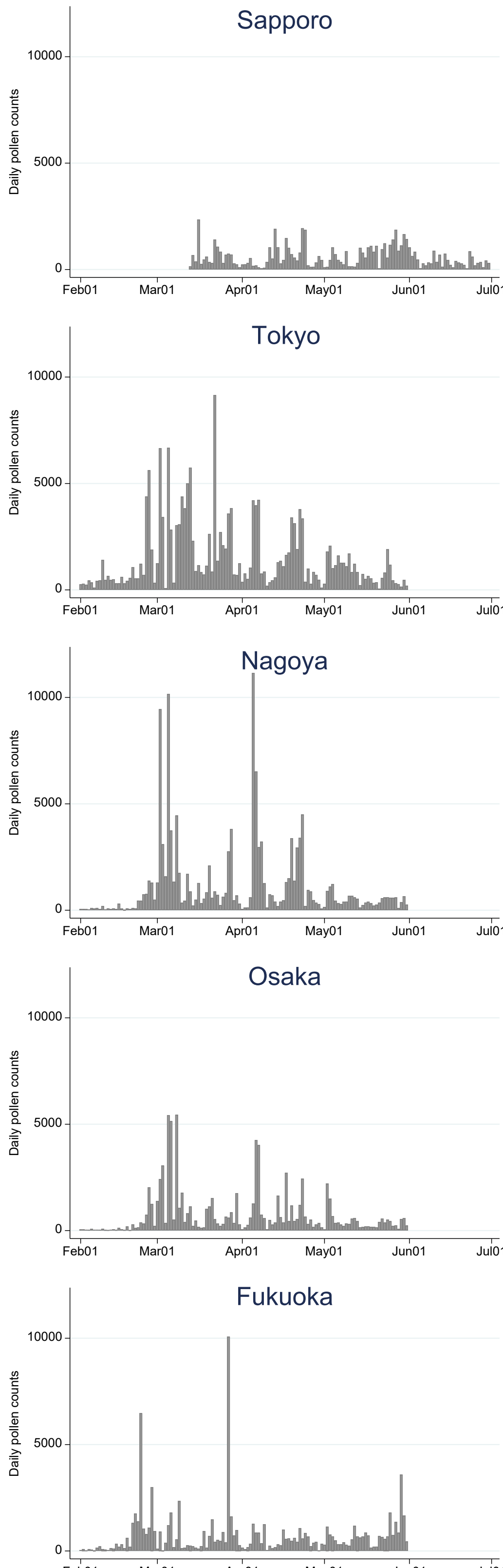
Notes: There are a total of 120 pollen stations in Japan. There are 47 prefectures in Japan, and on average each prefecture has 2 to 3 stations, except for Okinawa. Okinawa, which is located the furthest south, has a different climate from the rest of the country, and has no stations as pollen is not observed in Okinawa.

Figure A5—Distance to the pollen monitoring stations



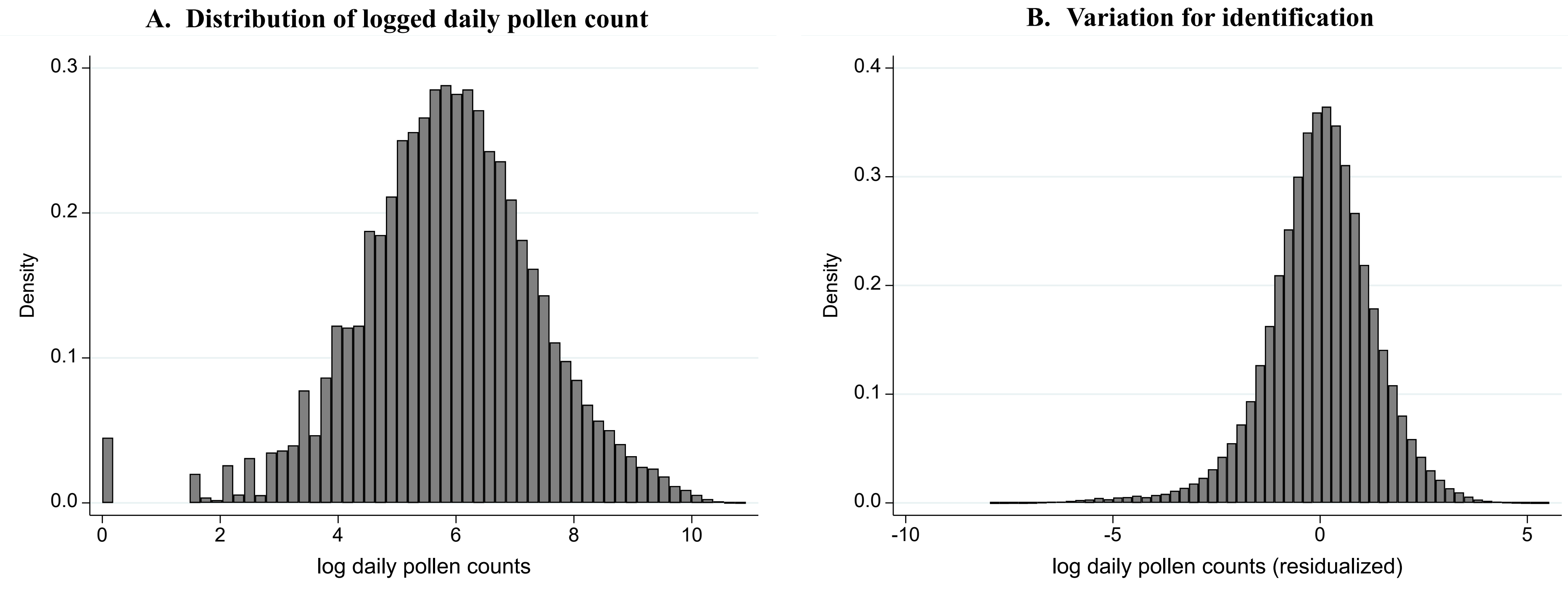
Notes: The figure plots the cumulative distribution of distance from the centroid of units (N=705) to the nearest pollen monitoring station (N= 120). The vertical dotted line corresponds to 48 km (30 miles) which is used by Chalfin et al. (2019). A total of 90.2% of stations (636 out of 705) are within this threshold.

Figure A6—Daily pollen counts for selected locations



Notes: The figure displays day-to-day variations in the daily pollen counts (grains/m^3) across five different locations from the north to the south of Japan in 2019. Sapporo, Tokyo, Nagoya, Osaka, and Fukuoka are located in the Hokkaido, Tokyo, Aichi, Osaka, and Fukuoka prefectures.

Figure A7—Variation in pollen counts



Notes: Panel A displays the histogram of the logged daily pollen count (grains/m^3) for the period 2008 to 2019. Panel B displays the histogram of log daily pollen count after residualized by the unit, month-by-year, month-by-prefecture, and day-of-week FEs.

Table A1—List of medications for seasonal allergy

Brand name in Japanese	Brand name in English	Year of release	Mention of driving
アレジオン	Alesion	1994	Careful driving required
エバステル	Evastel	1996	Careful driving required
ジルテック	Zyrtec	1998	Driving not allowed
タリオン	Talion	2000	Careful driving required
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 lists the brand names of allergy medications used to treat seasonal allergies together with the year of release of the medication as well as any particular mention of whether you are allowed to drive after taking the medication. The medications highlighted in gray are the ones that do not include any specific mention of driving after taking same. Note that our primary data on accidents spans from 2008 to 2019.

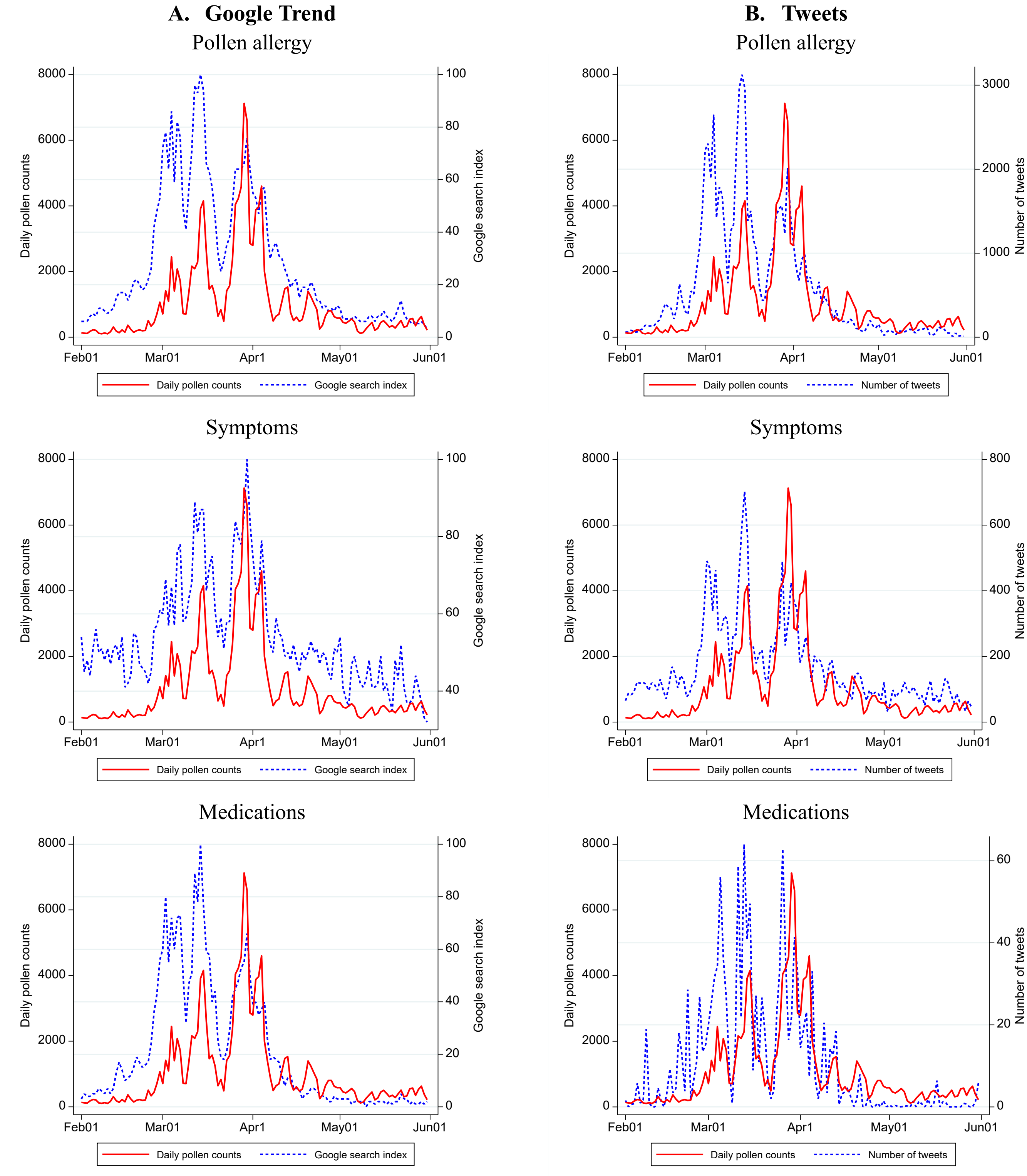
References:

Kishikawa, R. et al. 2020. "Pollen Calendar of Important Allergenic Airborne Pollen in Japan." (in Japanese) *Japanese Journal of Palynology*, 65(2): 55–66.

Japan Weather Association. 2022. https://tenki.jp/ (in Japanese) (accessed March 23, 2022).

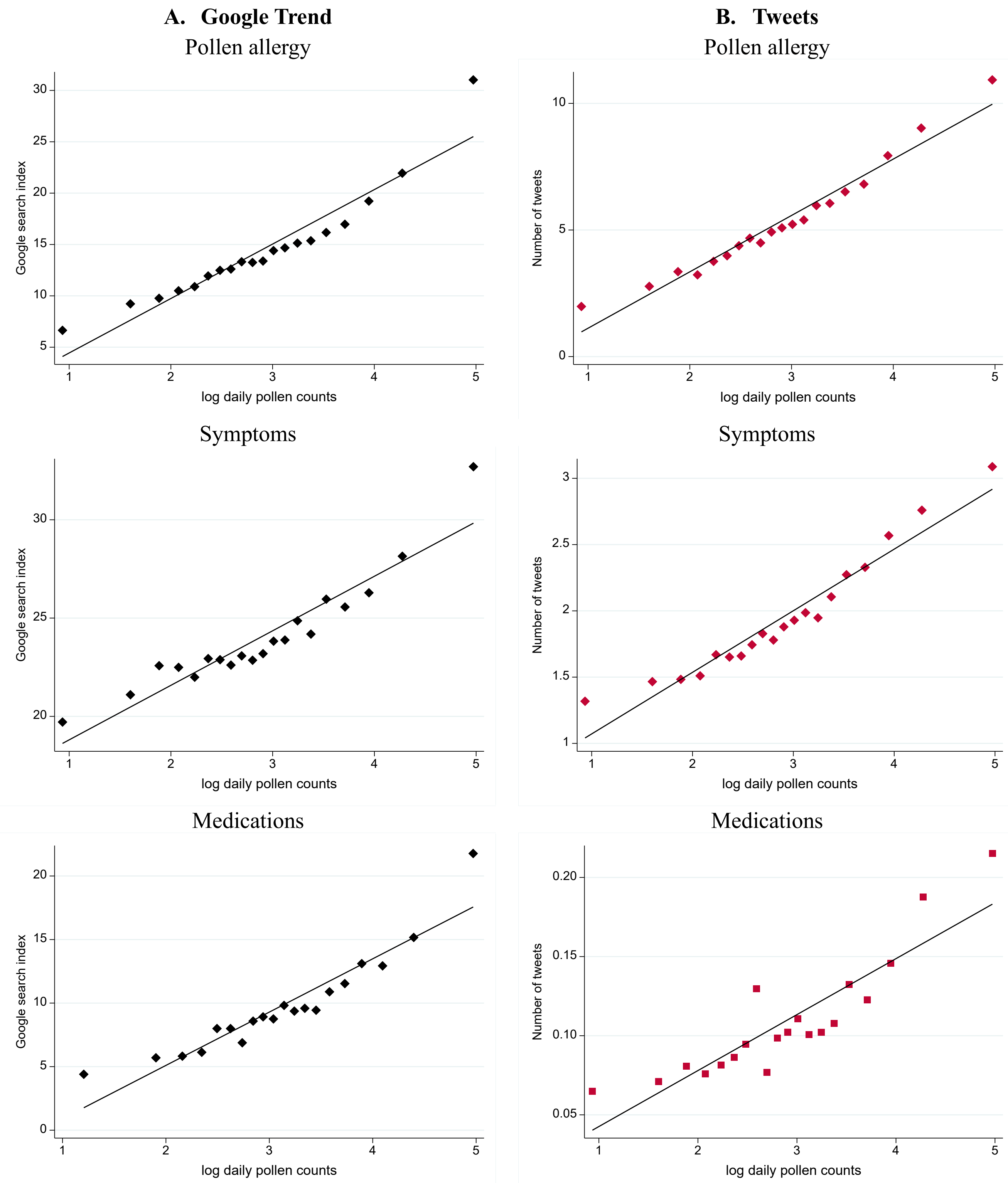
Appendix B: Google Trends and Tweets

Figure B1—Time series of daily pollen counts and Google Trend/Tweets



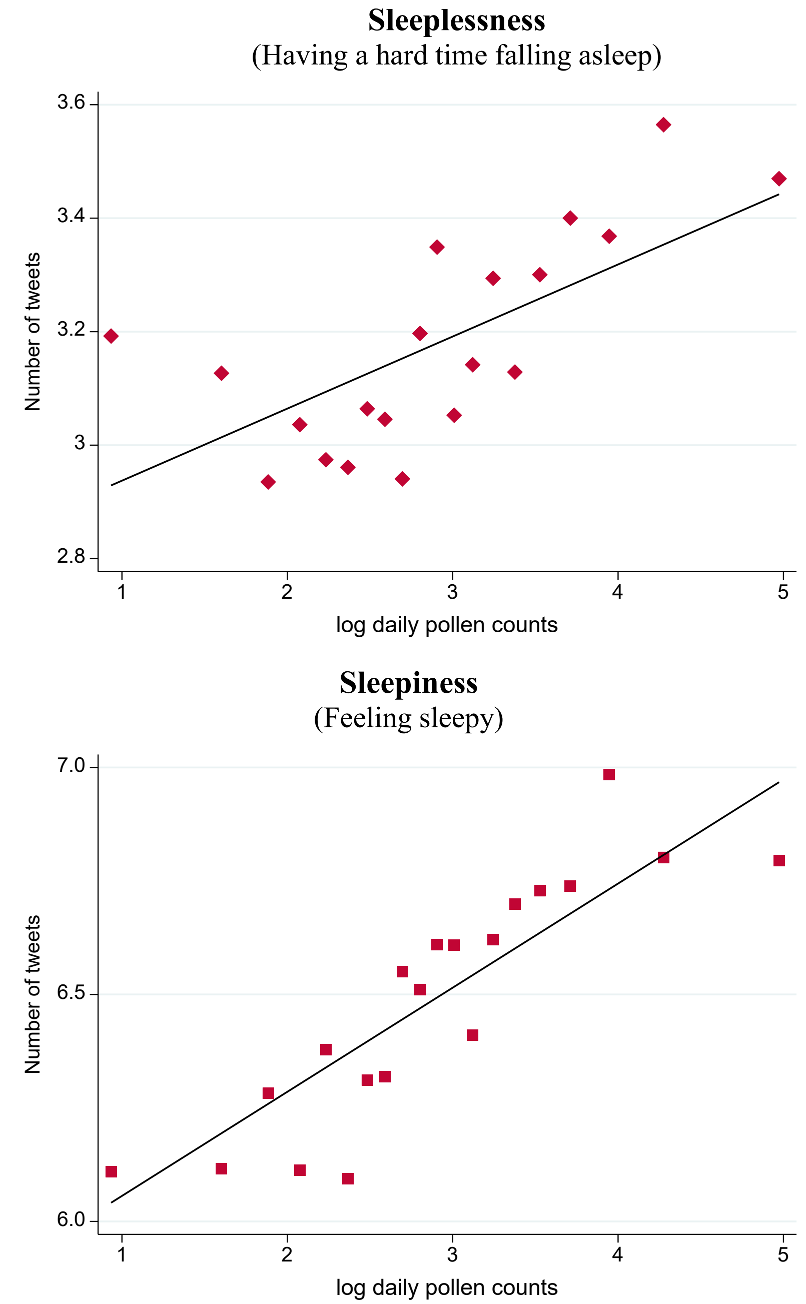
Notes: The figure shows the time series patterns of the average daily pollen counts (grains/m^3) and Google search index in Panel A and the number of Tweets for Panel B for pollen allergy-related, symptom-related, and medication-related keywords in 2018 at the country level. See Table B1 for the list of search keywords within each category. June is omitted as only four stations in Hokkaido (the northernmost island of Japan) are still operating in June.

Figure B2—Binscatter plot of pollen and Google Trend/Tweets



Notes: The sample derives from Google Trend data for the period 2016 to 2019 for Panel A and Twitter data for the period 2016 to 2019 for Panel B, and the level of observation is prefecture per day. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and Google search index in Panel A and the number of Tweets for Panel B for pollen allergy-related, symptom-related, and medication-related keywords, after controlling for the month-by-year, month-by-prefecture and day-of-week FE. See Table B1 for the list of search keywords within each category.

Figure B3—Binscatter plot of pollen and Tweets: sleep-related



Notes: The sample derives from Twitter data for the period 2016 to 2019, and the level of observation is prefecture per day. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the number of Tweets that include the terms "Hard time falling asleep" and "Sleepy" after controlling for the month-by-year, month-by-prefecture, and day-of-week FE. See Table B1 for the list of search keywords within each category.

Table B1—List of search keywords

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	Pollen of Japanese cedar
2	**Symptoms**	鼻水	Runny nose
		鼻づまり	Nasal congestion
		くしゃみ	Sneeze
		目のかゆみ	Itchy eyes
3	**Medications** (product name of popular allergy medications)	アレジオン	Alesion
		アレグラ	Allegra
		クラリチン	Claritin
Only for Tweets (sleep-related)			
4	**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	
5	**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 Japanese as well as English (for reference).

Table B2—Regression results on Google Trend/Tweets

	Panel A. Google Trend			Panel B. Tweets		
	(1)	(2)	(3)	(4)	(5)	(6)
Pollen allergy						
log (pollen)	5.716***	5.557***	4.083***	2.282***	2.056***	1.735***
	(0.233)	(0.219)	(0.215)	(0.671)	(0.485)	(0.601)
R-squared	0.64	0.66	0.78	0.48	0.70	0.51
N	21,551	21,551	21,433	21,551	21,551	21,433
Mean of dep. var	16.37	16.37	16.44	5.32	5.32	5.35
Symptoms						
log (pollen)	3.545***	3.400***	2.866***	0.489***	0.458***	0.401***
	(0.229)	(0.238)	(0.189)	(0.112)	(0.093)	(0.096)
R-squared	0.41	0.42	0.46	0.61	0.68	0.63
N	21,551	21,551	21,433	21,551	21,551	21,433
Mean of dep. var	30.40	30.40	30.34	1.95	1.95	1.94
Medications						
log (pollen)	3.763***	3.554***	2.536***	0.038***	0.032***	0.028**
	(0.294)	(0.259)	(0.231)	(0.013)	(0.009)	(0.011)
R-squared	0.42	0.45	0.52	0.21	0.29	0.23
N	21,551	21,551	21,433	21,551	21,551	21,433
Mean of dep. var	12.32	12.32	12.34	0.11	0.11	0.11
Prefecture FE	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X
Month-year FE	X		X	X		X
Month-prefecture FE		X			X	
Date FE			X			X

Notes: The sample derives from Google Trend data for the period 2016 to 2019 for Panel A and Twitter data for the period 2016 to 2019 for Panel B, and the level of observation is prefecture per day. The dependent variable is the Google search index for each category which takes the values from 0 to 100 in Panel A and the number of Tweets in Panel B. See Table B1 for the list of search keywords within each category. The estimates from the variants of Equation [1] are reported. The standard errors clustered at prefecture levels 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 B3—Regression results on Tweets: sleep-related

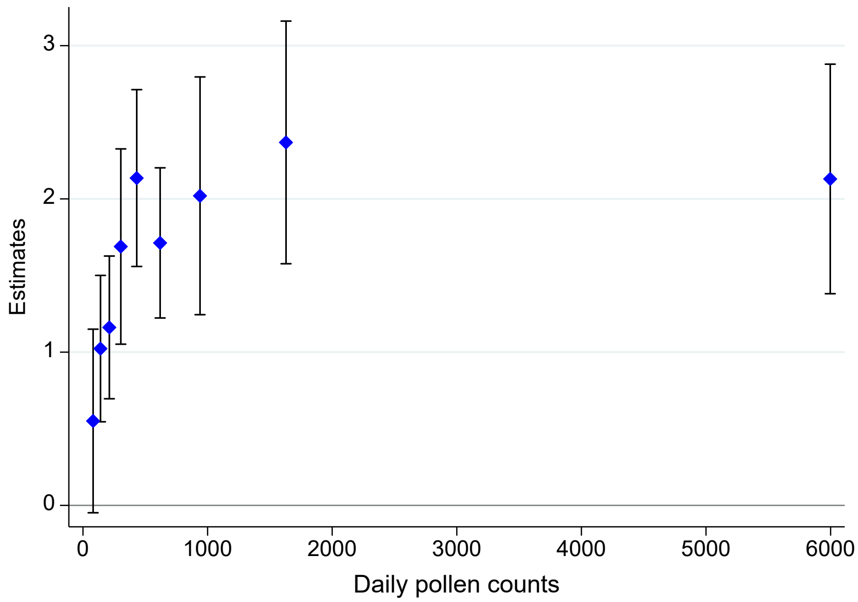
	(1)	(2)	(3)
Sleeplessness			
log (pollen)	0.138**	0.148**	0.130
	(0.057)	(0.062)	(0.078)
R-squared	0.72	0.72	0.73
N	21,551	21,551	21,433
Mean of dep. var	3.18	3.18	3.15
Sleepiness			
log (pollen)	0.171*	0.210**	0.174
	(0.089)	(0.093)	(0.118)
R-squared	0.84	0.84	0.84
N	21,551	21,551	21,433
Mean of dep. var	6.49	6.49	6.45
Prefecture FE	X	X	X
Day-of-week FE	X	X	X
Month-year FE	X		X
Month-prefecture FE		X	
Date FE			X

Notes: The sample derives from Twitter data for the period 2016 to 2019, and the level of observation is prefecture per day. The dependent variable is the number of Tweets. See Table B1 for the list of search keywords within each category. The estimates from the variants of Equation [1] are reported. The standard errors clustered at prefecture levels 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

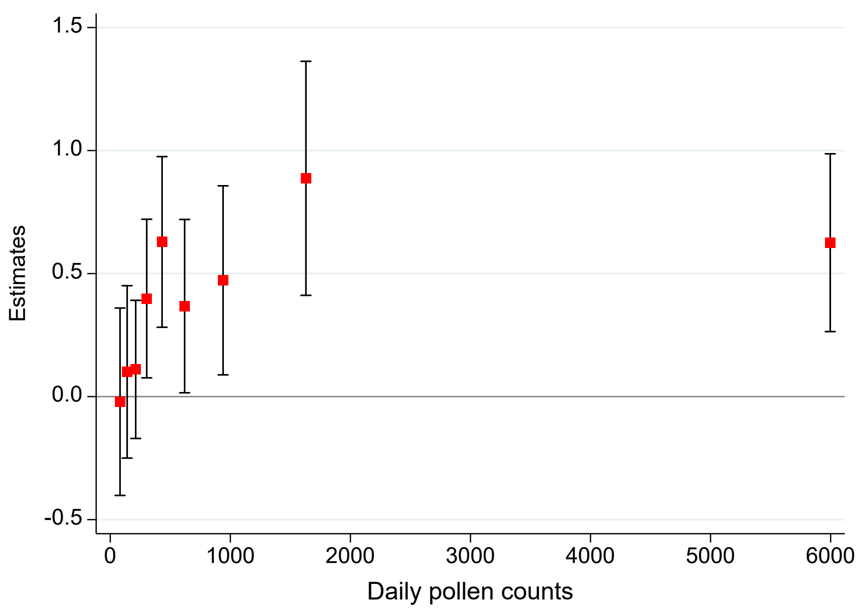
Appendix C: Ambulance Records

Figure C1—Dose responses

A. All accidents

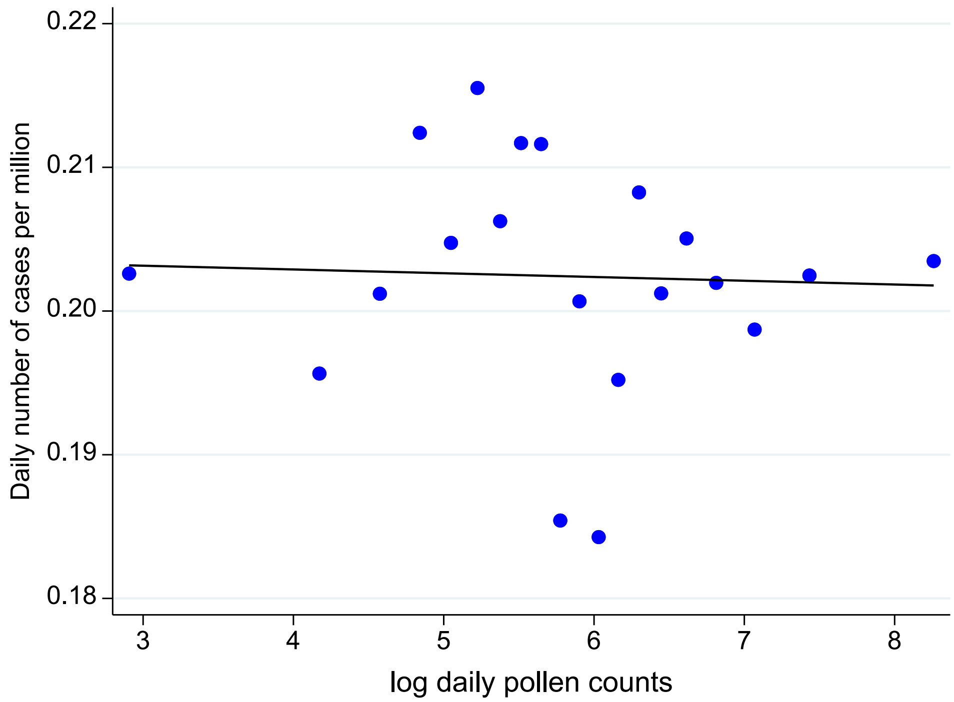


B. Traffic accidents



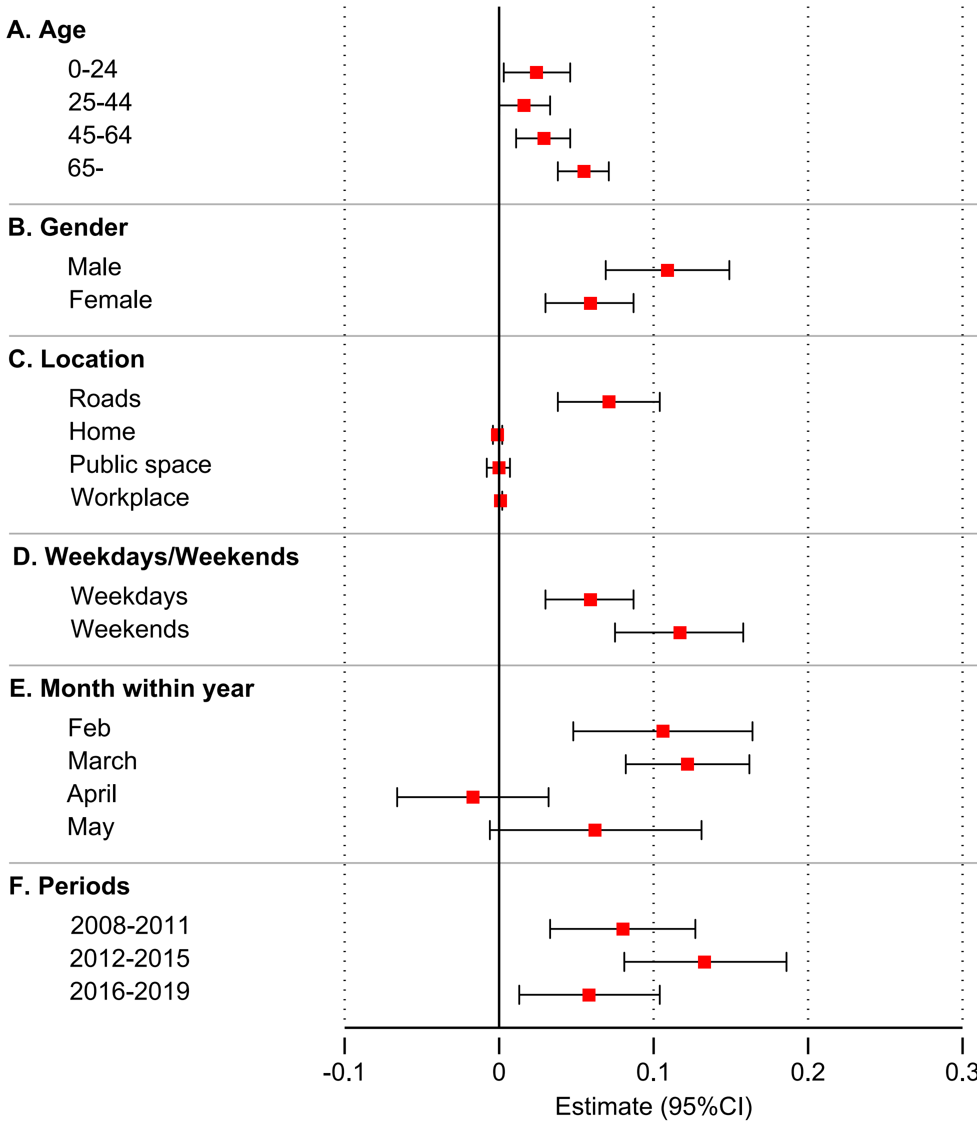
Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95% confidence interval of treatment effects of daily pollen count (in levels) from the variant of Equation [1], where the logged daily pollen is replaced by the dummies for each decile of daily pollen in levels. The dependent variable is the number of daily cases per million people for each accident type. The standard errors are clustered at pollen monitoring station levels. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. All specifications include 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. Estimates are weighted by the population in each unit.

Figure C2—Pollen and emergency ambulance transportation due to cancer



Notes: The sample derives from ambulance records for the period 2015 to 2019, and the level of observation is a unit per day (N = 407,463) since the ambulance records include detailed diagnosis information (equivalent to ICD10) from 2015 on. There are 705 units in total. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the number of daily emergency ambulance transportation due to cancer per million people, after controlling for the unit, month-by-year, month-by-prefecture, and day-of-week FEs.

Figure C3—Other heterogeneous treatment effects (Traffic accidents)

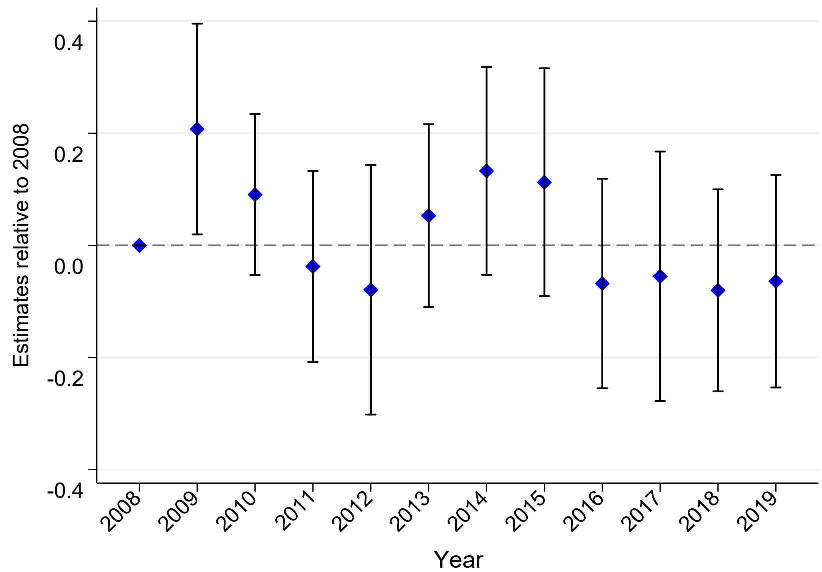


	Estimate (95%CI)	Mean	Rel. to mean
A. Age			
0-24	0.024 (0.003, 0.046)	3.12	0.78 %
25-44	0.016 (0.000, 0.033)	2.91	0.56 %
45-64	0.029 (0.011, 0.046)	2.83	1.01 %
65-	0.055 (0.038, 0.071)	2.65	2.06 %
B. Gender			
Male	0.109 (0.069, 0.149)	6.36	1.72 %
Female	0.059 (0.030, 0.087)	4.70	1.25 %
C. Location			
Roads	0.071 (0.038, 0.104)	6.54	1.09 %
Home	-0.001 (-0.004, 0.002)	0.07	-1.58 %
Public space	0.000 (-0.008, 0.007)	0.16	-0.12 %
Workplace	0.001 (0.000, 0.002)	0.01	6.30 %
D. Weekdays/Weekends			
Weekdays	0.059 (0.030, 0.087)	12.46	0.47 %
Weekends	0.117 (0.075, 0.158)	12.29	0.95 %
E. Month within year			
Feb	0.106 (0.048, 0.164)	11.89	0.89 %
March	0.122 (0.082, 0.162)	12.35	0.99 %
April	-0.017 (-0.066, 0.032)	12.75	-0.13 %
May	0.062 (-0.006, 0.131)	12.75	0.49 %
F. Periods			
2008-2011	0.080 (0.033, 0.127)	13.65	0.59 %
2012-2015	0.133 (0.081, 0.186)	12.51	1.07 %
2016-2019	0.058 (0.013, 0.104)	11.14	0.52 %

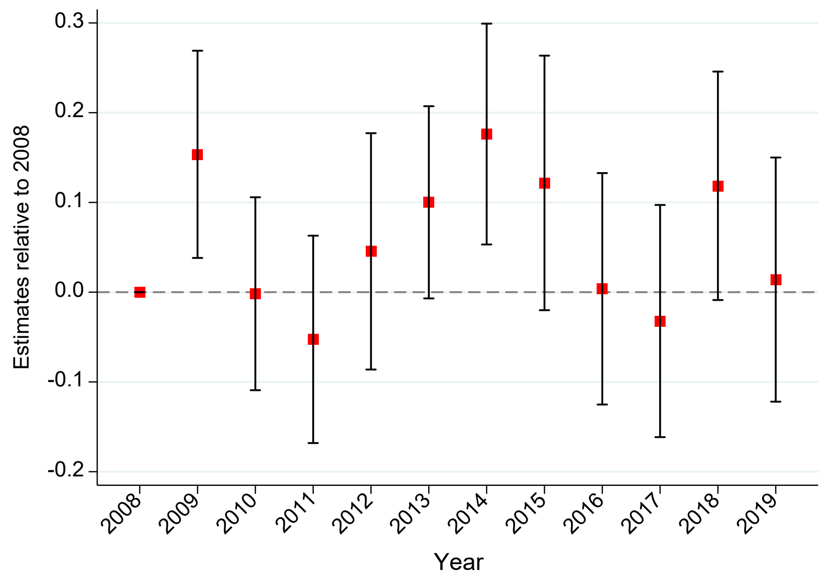
Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95% confidence interval of heterogeneous treatment effects of logged daily pollen count from Equation [1]. The standard errors are clustered at pollen monitoring station levels. The dependent variable is the number of daily cases of accidents per million people using all accident data. The share of traffic accidents among all accidents is 37.6%. The mean reported second to the far right is the number of daily cases per million people. The relative to the mean reported on the far right is the estimate divided by the mean.

Figure C4—Treatment effects over time (relative to 2008)

A. All accidents



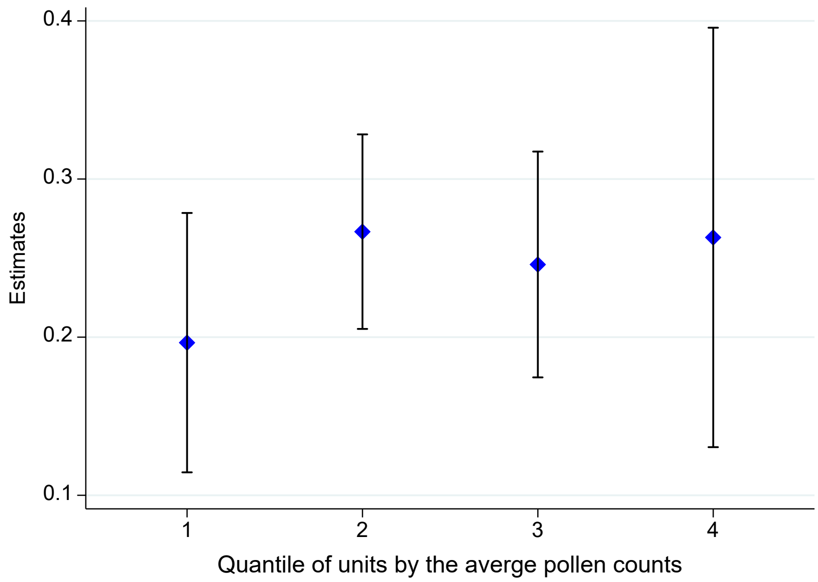
B. Traffic accidents



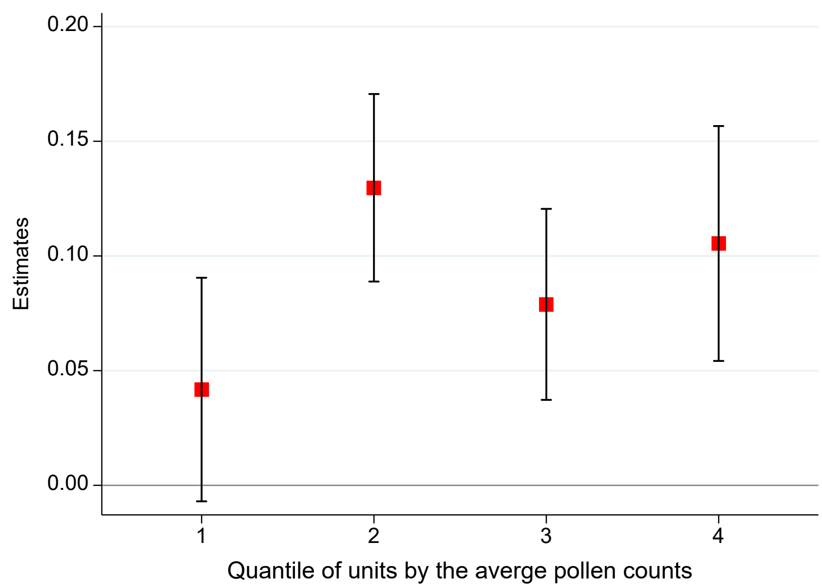
Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. We add a series of interaction terms of logged daily pollen count with each year dummy from 2009 to 2019 (2008 as baseline). The graph displays the estimates of a series of interaction terms, that capture the treatment effects of logged daily pollen count *relative to* the treatment effects in 2008, along with a 95% confidence interval. The dependent variable is the number of daily cases per million people for each accident type. The standard errors are clustered at pollen monitoring station levels. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. All specifications include 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. Estimates are weighted by the population in each unit.

Figure C5—Treatment effects by high vs. low pollen regions

A. All accidents



B. Traffic accidents



Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95% confidence interval of heterogeneous treatment effects of logged daily pollen count from Equation [1]. The dependent variable is the number of daily cases per million people for each accident type. The standard errors are clustered at pollen monitoring station levels. We calculate the average pollen counts during the period 2008 to 2019 for each unit and divide the units into quantiles. A lower quantile indicates that the units have low average pollen concentrations, while a higher quantile indicates that the units have high average pollen concentrations. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. All specifications include 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. Estimates are weighted by the population in each unit. The mean (median) pollen counts (grains/m^3) at each quantile are 66(68), 238(232), 587(559), and 3260(1871), respectively.

Table C1—Different time FE

	(1)	(2)	(3)	(4)	(5)	(6)
A. All accidents						
log (pollen)	0.231***	0.217***	0.235***	0.241***	0.280***	0.331***
	(0.020)	(0.019)	(0.020)	(0.020)	(0.022)	(0.024)
R-squared	0.46	0.46	0.46	0.47	0.46	0.49
N	970,309	970,309	970,309	970,309	970,309	969,623
Mean of dep. var	33.03	33.03	33.03	33.03	33.03	33.03
B. Traffic accidents						
log (pollen)	0.079***	0.079***	0.091***	0.084***	0.118***	0.140***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)
R-squared	0.24	0.24	0.24	0.24	0.24	0.27
N	970,309	970,309	970,309	970,309	970,309	970,306
Mean of dep. var	12.41	12.41	12.41	12.41	12.41	12.41
Unit FE	X	X	X		X	
Day-of-week FE	X	X	X	X	X	X
Month-year FE	X		X	X		
Month-prefecture FE	X	X				
Month & Year FE		X				
Month-unit FE				X		
Month-year-prefecture FE					X	
Month-year-unit FE						X

Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N = 970,309). There are 705 units in total. The dependent variable is the number of daily cases per million people for each accident type. The estimates from Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. In addition to the fixed effects in the table, we include weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Column (1) replicates the results from Table 2 (baseline) for ease of comparison. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table C2—Different levels of clustering

Clustering variables	N of clusters	A. All accidents		B. Traffic accidents	
		0.231		0.079	
Monitoring stations (baseline)	120	(0.020)	***	(0.012)	***
Monitoring stations and date	120 + 1796	(0.028)	***	(0.016)	***
Monitoring stations and month-year	120 + 60	(0.030)	***	(0.019)	***
Unit	705	(0.019)	***	(0.012)	***
Unit and date	705 + 1796	(0.028)	***	(0.016)	***
Unit and month-year	705 + 60	(0.031)	***	(0.019)	***
Prefecture	47	(0.016)	***	(0.012)	***
Prefecture and date	47 + 1796	(0.025)	***	(0.015)	***
Prefecture and month-year	47 + 60	(0.028)	***	(0.018)	***

Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). The dependent variable is the number of daily cases per million people for each accident type. The estimates from Equation [1] are reported. All specifications include 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. The number of pollen monitoring stations, units, and prefectures are 120, 705, and 46, respectively. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. 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)
A. All accidents			
log (pollen)	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
B. Traffic accidents			
log (pollen)	0.079***	0.0056***	0.013***
	(0.012)	(0.0010)	(0.002)
R-squared	0.24	0.80	-
N	970,309	970,309	970,309
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-year FE	X	X	X
Month-prefecture FE	X	X	X

Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. Column (1) replicates the results from Table 2 (baseline) for ease of comparison. Column (2) reports the estimates from variants of Equation [1], where the dependent variable takes the log 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 the Poisson pseudo-maximum likelihood (PPML) (*dydx* command in Stata). The standard errors clustered at pollen monitoring station levels 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
A. All accidents			
log (pollen)	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
B. Traffic accidents			
log (pollen)	0.079***	-0.018	-0.002
	(0.012)	(0.012)	(0.011)
R-squared	0.24	0.24	0.24
N	970,309	879,777	881,226
Mean of dep. var	12.41	12.27	12.59
Unit FE	X	X	X
Day-of-week FE	X	X	X
Month-year FE	X	X	X
Month-prefecture FE	X	X	X

Notes: The sample derives from ambulance records for the period 2008 to 2019, and the level of observation is a unit per day. There are 705 units in total. The dependent variable is the number of daily cases per million people for each accident type. The estimates from Equation [1] are reported. All specifications include 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. Column (1) replicates the results from Table 2 (baseline) for ease of comparison. Columns (2) and (3) assign pollen levels of the same day in a previous year and the following year (e.g., for March 3, 2018, in unit *X*, Columns (2) and (3) assign the pollen levels on March 3, 2017, and March 3, 2019, in the same unit *X*.) The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

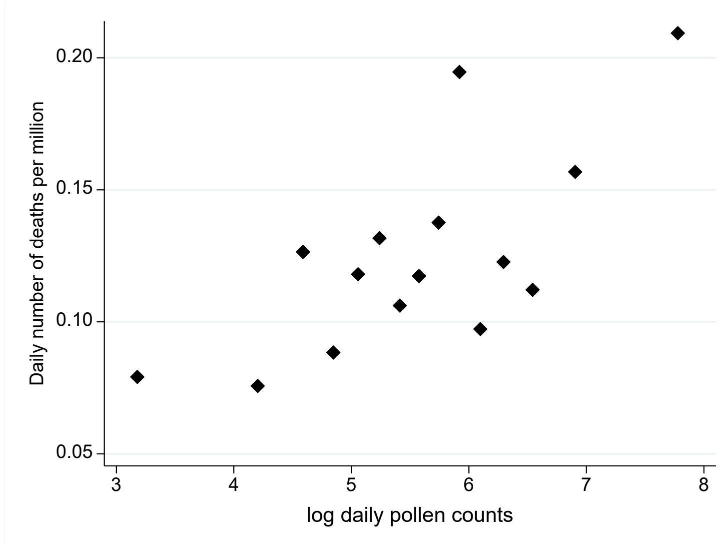
Appendix D: Police Records

Police records contain all 690,415 (or 106,533 in pollen season) traffic accidents for the period 2019 to 2020. The data is at the individual level of accident and includes information on the location, date and time the accident occurred. Unlike the ambulance service, where the unit of service is a unit (N= 705), the police service is administered at the municipality level (N= 1,700). Thus, we aggregate the number of casualties to the municipality-day level by adding the hourly observations within the municipalities.

Figure D1 displays the binscatter plots of the relationship between the logged average daily pollen counts (grains/m^3) and the number of deaths from traffic accidents per million people after controlling for municipality, month-by-year, month-by-prefecture, and day-of-the-week FEs. The figure clearly shows the positive relationship between the two variables.

Table D1 reports the estimates from Equation [1], where the unit FE is replaced by municipality FE. For ease of comparison, Column (1) replicates the death/fatal estimates for traffic accidents during the period 2008 to 2019 ambulance records (from the first row of Panel B in Figure 4). Column (2) reports the mortality estimates during 2019 to 2020 police records. The estimate of 0.0040 (p-value<0.01) in Column (2) is larger than the estimate of 0.0026 from Column (1), indicating that we may have slightly underestimated the effect of pollen exposure on the number of deaths as a result of traffic accidents. However, the two estimates are not statistically distinguishable at the conventional level.

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



Notes: The sample derives from police records for the period 2019 to 2020, and the level of observation is municipality per day (N = 399,749). There are 1,700 municipalities in total. The graph displays the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the number of deaths per million people within 24 hours as a result of traffic accidents after controlling for municipality, month-by-year, month-by-prefecture, and day-of-week FEs.

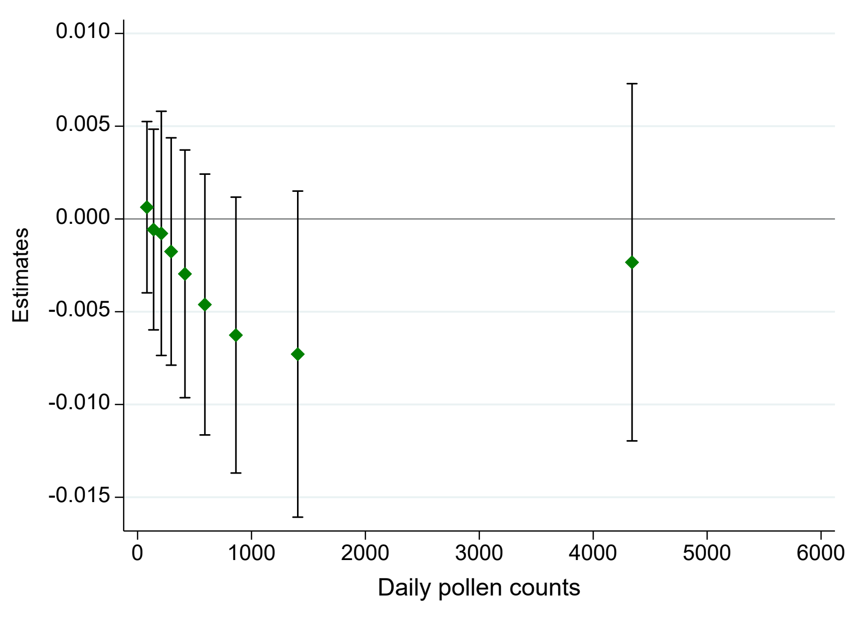
Table D1—Mortality as a result of traffic accidents (ambulance records vs. police records)

	Ambulance Record	Police Record
	(1)	(2)
log (pollen)	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	0.16	0.12
Unit/municipality FE	X	X
Day-of-week FE	X	X
Month-year FE	X	X
Month-prefecture FE	X	X

Notes: The sample for Column (1) derives from ambulance records for the period 2008 to 2019, while the sample for Column (2) derives from police records for the period 2019 to 2020. The level of observation is unit per day for Column (1) and municipality per day for Column (2). There are 705 units and 1,700 municipalities in total. The dependent variable is the number of deaths as a result of traffic accidents per million people. The estimates from Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. In addition to the fixed effects in the table, we include weather covariates (precipitation, temperature, wind speed), darkness, and logged population. Column (1) is identical to the first row of Panel B in Figure 4. 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 Behaviors

Figure E1—Dose responses of avoidance behaviors (weekends only)



Notes: The sample is derived from cell-phone location data for the period 2014 to 2019, and the level of observation is a unit per day (N =478,853). There are 705 units in total. The graph displays the estimates and 95% confidence interval of treatment effects of daily pollen count (in levels) from the variant of Equation [1], where the logged daily pollen is replaced by the dummies for each decile of daily pollen in levels. The dependent variable is the logged daily number of people outside at 2pm. The standard errors are clustered at pollen monitoring station levels. All specifications include 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. Estimates are weighted by the population in each unit.

Table E1—Outdoor population and accidents

	A. All accidents			B. Traffic accidents		
	All	Weekdays	Weekends	All	Weekdays	Weekends
	(1)	(2)	(3)	(4)	(5)	(6)
log (number of outdoor population)	0.9597**	0.4645	2.0066**	0.4835**	0.5532**	1.0239***
	(0.4181)	(0.4411)	(0.7745)	(0.2241)	(0.2537)	(0.3407)
R-squared	0.49	0.48	0.51	0.24	0.24	0.23
N	478,853	343,454	135,399	478,853	343,454	135,399
Unit FE	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X
Month-year FE	X	X	X	X	X	X
Month-prefecture FE	X	X	X	X	X	X

Notes: The sample derives from ambulance records for the period 2014 to 2019 that are matched to "Mobile Spatial Statistics" data provided by NTT DOCOMO, Inc at the unit-day level (N= 478,853). There are 705 units in total. The share of traffic accidents (Panel B) among all accidents (Panel A) is 37.6%. The estimates from regressing the number of daily accidents per million people (our main outcome) on the logged number of outdoor population, with the same sets of FEs and controls as an Equation [1] (excluding logged number of pollen counts), are reported. The standard errors clustered at pollen monitoring station levels are reported in parentheses. Columns (2) and (5) restrict the samples to weekdays, and Columns (3) and (6) restrict the samples to weekends. Estimates are weighted by the population in each unit. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table E2—Avoidance behaviors with full covariates

	A. All	B. By type of day	
		Weekdays	Weekends
	(1)	(2)	(3)
log (pollen)	-0.0005	0.0000	-0.0021***
	(0.0006)	(0.0006)	(0.0007)
Rain (base: no rain)			
<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)
log (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
Pref FE	X	X	X
Day-of-week FE	X	X	X
Month-year FE	X	X	X
Month-prefecture FE	X	X	X

Notes: The sample derives from cell-phone location data for the period February to May for the years 2014 to 2019, and the level of observation is a unit per day. There are 705 units in total. The estimates from variants of Equation [1] are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. The dependent variable is the logged daily number of people outside at 2pm. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table E3—Controlling avoidance behaviors for all accidents (weekdays vs. weekends)

	A. Weekdays		B. Weekends	
	(1)	(2)	(3)	(4)
log (pollen)	0.1735***	0.1736***	0.2692***	0.2733***
	(0.0328)	(0.0329)	(0.0585)	(0.0589)
log (number of outdoor population)		0.4640		2.0526***
		(0.4418)		(0.7751)
R-squared	0.48	0.48	0.51	0.51
N	343,483	343,454	135,422	135,399
Unit FE	X	X	X	X
Day-of-week FE	X	X	X	X
Month-year FE	X	X	X	X
Month-prefecture FE	X	X	X	X

Notes: The sample derives from ambulance records for the period 2014 to 2019 that are matched to "Mobile Spatial Statistics" data provided by NTT DOCOMO, Inc at the unit-day level. There are 705 units in total. The estimates from Equation [1], separately for weekdays in Panel A and weekends in Panel B, are reported along with the standard errors clustered at pollen monitoring station levels in parentheses. The dependent variable is the number of all daily accidents per million people. Columns (2) and (4) add the logged number of outdoor population at 2pm to Columns (1) and (3), respectively. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Appendix F: 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 in respect of accidents that involve 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 pollen seasons (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 pollen seasons) 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, PM10 Source: National Institute for Environmental Studies https://www.nies.go.jp/igreen/index.html
Geolocation data	Years: 2014–2019 Data description: called "Mobile Spatial Statistics" data which are estimates based on the location information of 85 million NTT DOCOMO cell-phone users (as of March 2022) Source: NTT DOCOMO, Inc https://mobaku.jp/ (in Japanese)