"Invisible Killer": Seasonal Allergy and Accidents[*]

Mika Akesaka[†]
Kobe University

Hitoshi Shigeoka[‡]
Simon Fraser University, University of Tokyo, and NBER

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Abstract

Despite at least 400 million seasonal allergy sufferers worldwide, the adverse impacts of pollen on 'non-health' outcomes such as cognition and productivity are surprisingly understudied. Using the universe of ambulance records in Japan, we are the first to show that high pollen days are associated with more accidents—the most extreme consequence of cognitive impairment. Using geolocation data, we find limited evidence of avoidance behaviors, implying that the risk of pollen exposure is severely discounted. Finally, the increased pollen concentrations due to climate change are projected to aggravate pollen-induced accidents, with a minimum social cost of USD231 million annually.

Keywords: Seasonal allergy, Pollen, Accidents, Cognition, Avoidance behaviors, Adaptation, Climate change
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[†] Kobe University, Research Institute for Economics and Business Administration, 2-1, Rokkodai, Nada, Kobe, Hyogo, 657-8501, JAPAN. Email: mika_akesaka@rieb.kobe-u.ac.jp

[‡] Corresponding author: Simon Fraser University, Department of Economics, 8888 University Drive, Burnaby, BC V5A1S6, CANADA, University of Tokyo, Graduate School of Public Policy, IZA, and NBER. Email: hitoshi_shigeoka@sfu.ca

1. Introduction

"Hay fever," or seasonal allergic rhinitis (SAR) as 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 an industrialized country, with an estimated 400 million sufferers worldwide (Greiner et al. 2011; Schmidt 2016). Despite its global scale, the adverse impact of pollen receives surprisingly little attention from economists, probably due to the following two reasons. First, the symptoms are relatively mild and chronic such as runny nose, nasal congestion, sneezing, and itchy eyes. However, the very non-acute physiological effects of pollen can be potentially problematic because people do not engage in serious ex-ante avoidance behaviors to limit exposure.

Second, in sharp contrast with *man-made* air pollution, the scope of policy intervention for exposure to *natural* sources like pollen is seemingly limited.[1] However, a very recent study projects that global warming will accelerate pollen production and hence increase the pollen concentrations (16–40%) and prolong the duration of pollen seasons (+19 days) in the United States (Zhang and Steiner 2022). Figure 1 confirms the strong positive associations between pollen counts and maximum temperature (Panel A) and the number of hot days (Panel B) in the previous summer in Japan—our study setting. Although pollen is a natural phenomenon, human-caused climate change can exacerbate the potential damage from pollen exposure.

Importantly, clinical studies identify the detrimental effect of pollen exposure on cognitive performance through lower attention span and longer reaction time (e.g., 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 should have much more significant consequences—beyond just children and test scores. Since pollen exposure severely inhibits cognitive functioning, any sensible human daily activities can be affected.

We conduct the first investigation of the effects of acute and short-term pollen exposure on the incidence of accidents—arguably one of the most extreme consequences of cognitive

[1] Economists have accumulated knowledge on the impact of exposure to air pollution on a variety of outcomes ranging from health, human capital, labor productivity, and crime, to name a few. See Graff Zivin and Neidell (2013) and Aguilar-Gomez et al. (2022) for excellent summaries of the literature.
[2] An exception is Chalfin et al. (2019) which document that violent crime *declines* in the U.S. cities on days with unusually high pollen counts, potentially because people may spend less time outdoors on high pollen days.

impairment—including traffic and work-related injuries. For example, safe driving is a complex and cognitively demanding task, and past studies document that cognitive performance is negatively correlated with the likelihood of car crashes (Anstey et al. 2005, 2012). Similarly, the most common cause of workplace injury is distraction (European Commission 2009).

We combine the pollen counts with the newly available administrative ambulance records that cover the universe of accidents from 2008 through 2019 in Japan. These accidents are especially severe as they require ambulance transportation to hospitals. Japan is an ideal setting to answer this question as the pollen monitoring stations are densely located across the country (42 times higher than the United States), and 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 can provide nationally representative estimates, unlike previous studies that limit only to a handful of schools or districts near pollen stations, which mitigates concerns about generalizability. 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 fire accidents.[3] We document important heterogeneous responses to pollen exposure. While the effects are more pronounced for less severe accidents, the elevated pollen exposure also increases accidents that lead to death. The effect is also more pronounced for the elderly than the non-elderly, consistent with the higher vulnerability of the elderly to environmental externalities.[4] Interestingly, we find larger effects on the weekends than on the weekdays, hinting at the limited avoidance behaviors as most people should have more discretions to avoid exposure (e.g., remaining indoors) relatively more easily on weekends than on weekdays.

Second, we indeed find some but limited evidence of short-term avoidance behaviors to

[3] 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 allergy). 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.

[4] See, for example, Barwick et al. (2019), Carleton and Solomon (2016), Carleton et al. (2022), Cohen and Dechezleprêtre (2022), and Jia and Ku (2019).

curtail pollen exposure. Since pollen size is relatively large ($\approx 30\ \mu m$), unlike PM2.5, the low-cost and effective solution is simply staying indoors to avoid exposure on high pollen days. Using geolocation data from Japan's largest mobile phone carriers, we find some but very limited evidence of reducing outdoor activities on high pollen days. This finding sharply contrasts with the case of ambient pollution, where avoidance behaviors mitigate the adverse effect of pollution on respiratory hospital admissions by 40% and 160% for the elderly and children, respectively (Neidell 2009).

Third, we also fail to find strong evidence of medium-term adaptation potential to the adverse impact of pollen exposure. The fundamental question on environmental hazards is whether such hazards are mostly unavoidable or whether people can adapt by using the current technologies.[5] In our context, more recent medications for seasonal allergies have a lesser side effect of drowsiness, which might reduce the risk of drowsy driving. Also, one may engage in defensive investment (e.g., purchase of an air purifier) during a more extended period. Here, we investigate whether the detrimental effect of pollen exposure has declined in more recent years. At least during the 12 years of our sample period, while the estimates become slightly smaller in very recent years (all p-values<0.01), the magnitude of the decline is marginal. Furthermore, we find that individuals who live in the higher pollen regions, on average, are similarly affected as those who live in the lower pollen regions.

Finally, we combine our estimates 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 IPCC—which predicts an increase of 4.2℃ in the summer temperature in the years 2071–2100 in Japan—leads to 1785 additional pollen-induced accidents, including 30 deaths 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 $231 million. This estimated social cost of pollen-induced accidents is very likely to be lower bound because we miss the accidents at both sides of severity distribution (i.e., minor cases as well as immediate deaths) that did not even require ambulance transportation to hospitals.

This paper has several policy implications. First, we show that exposure to pollen can affect beyond the school performance of children, suggesting that pollen concentration might

[5] 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).

have much broader impacts on cognition, productivity, and daily human activities more generally than 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, based mainly on easy-to-measure health outcomes, school missing days, and work absenteeism, may severely underestimate the true cost of pollen-induced seasonal allergy to society.

Second, the limited short-term avoidance behaviors, despite rich information access to daily pollen levels, indicate that the cognitive risk of pollen exposure is severely discounted. The real-time pollen information is commonly reported in the weather forecast on TVs and newspapers, and many apps and websites also provide pollen forecasts in our sample period. Thus, government intervention that raises the *salience* of risk that pollen exposure poses to their health and cognition might be warranted in addition to providing timely pollen information. For example, the public information campaigns such as "pollen alert"—recommending curtailing outdoor activities, wearing particulate-filtering masks, and taking public transportation on high pollen days—can be a possibly cost-effective tool to reduce pollen-induced accidents.[6]

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 and mortality, and agricultural outcomes (Carleton and Solomon 2016; Dell et al. 2014), the increases in seasonal allergy sufferers and associated productivity loss can be the indirect and undiscovered cost of the anthropogenic climate change. Consequently, any measure to mitigate the risk of a warming climate could have substantial social benefits.

The rest of the paper is organized as follows. Section 2 briefly describes the background. Section 3 describes the data, and section 4 presents the econometric model. Section 5 reports our findings. Section 6 projects the damage from climate change. Section 7 concludes.

2. Background

2.1. Pollen and seasonal allergy

Seasonal allergic rhinitis (SAR), widely known as "fay fever," is a common chronic condition. SAR occurs when people's immune system reacts to allergens in the air, such as pollen and dust, causing the immune system to produce antibodies (like histamine and

[6] A similar alert of ozone and ambient air pollution successfully boost avoidance (e.g., Anderson et al. 2022; Neidell 2009).

cytokines) to fight the perceived threat from the pollen grains. The antibodies will, in turn, cause an inflammatory state in the airways, inducing various allergic symptoms like runny nose, nasal congestion, sneezing, and itchy eyes (Greiner et al. 2012).

SAR is a global health problem as otherwise seemingly healthy people can be affected by SAR, thereby broadening its impact (Bousquet et al. 2008). The prevalence rates vary by country but are generally between 10–40% in industrialized countries, with an estimated 400 million sufferers worldwide (Greiner et al. 2011; Schmidt 2016). Furthermore, many studies document increasing prevalence due to various factors such as urbanization and westernization of lifestyles, and climate change, as we discuss more in detail in the following subsection.

Japan is not an exception; an extensive epidemiological survey for otolaryngologists and their families has been conducted every ten years (1998, 2008, and 2019), guided by the Japan Society of Immunology and Allergology in Otolaryngology. According to the 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, and it peaks around middle age, but the substantial fraction of young and old people also suffer; 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–) in 2019 (Matsubara et al. 2020). Also, the prevalence rate is particularly high in urban areas; in Tokyo, it increased from 19.4% in 1996 to as high as 48.8% in 2016, meaning that one out of two residents in Tokyo may suffer from SAR (Tokyo Metropolitan Institute of Public Health 2017).

Due to relatively mild and chronic symptoms, the economic cost of SAR 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 at work and missed school days (Hellgren et al. 2010; Lamb et al. 2006).[7]

Most relevant to this study, clinical studies identify the adverse effect on cognitive performance—indirectly by 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, including longer response times,

[7] Arrighi et al. (1996) estimated that US schoolchildren lose around 2 million school days per year due to allergic symptoms from pollen, including lack of sleep, somnolence in the daytime, and concentration problems. A few studies have estimated the annual per capita cost of SAR to be in the range of $600 to $1000, taking into account direct medical costs and indirect costs due to absenteeism (Hellgren et al. 2010; Lamb et al. 2006).

reduced working memory, divided attention, and slower computation. Unfortunately, medical studies have shown that allergy medications can induce similar or even stronger adverse effects on cognitive functioning because of various side effects, such as drowsiness, dry mouth, and lethargy (Jáuregui et al. 2009; Kay 2000).

Thus far, the existing studies of seasonal allergy on cognition and productivity in the field setting are limited to its effect on the test performance of children (Bensnes 2016; Marcotte 2015, 2017). However, since pollen exposure impairs cognitive performance, any sensible human daily activities can be severely affected. In this paper, we focus on accidents, including traffic and work-related injuries, as they are arguably one of the most extreme failures induced by cognitive impairment. For example, it is well-established that cognitive function is negatively correlated with the likelihood of car crashes (Anstey et al. 2005, 2012).[8]

In sum, while scientific knowledge about the impact of other environmental stressors (such as pollution and temperature) on cognitive performance and productivity has been accumulated[9], the impact of airborne pollen and associated seasonal allergies on cognitive performance and productivity is understudied. It is rather surprising given the global scale of from seasonal allergy sufferers and potentially enormous social costs.

2.2. Warming temperature and pollen

Since temperature and CO_2 concentrations have been found to increase pollen production, climate change is expected to impact pollen concentrations and durations of pollen seasons significantly. Anderegg et al. (2021) tracked pollen trends across 60 pollen stations in the US from 1990 to 2018 and found 20.9% and 21.5% increases in annual and spring (February–May) pollen concentrations, as well as advances of 20 days in pollen season start date and lengthening of the pollen season by eight days. Interestingly, they conducted a model selection analysis to identify the main drivers of pollen proliferation and found that among eight climate variables (including temperature, precipitation, frost days, and CO_2 concentrations), mean annual temperature was the strongest predictor of the above-mentioned pollen metrics. Increased pollen quantities, advancement of pollen season starting date, and

[8] Smith (2016) also demonstrates that a one-hour sleep loss increases the probability of being in a drowsiness-related fatal car crash by 46 percent.
[9] 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).

prolonged duration of the pollen season are similarly observed in Europe (Ziello et al. 2012; Hamaoui-Laguel et al. 2015).

We confirm that such a relationship between the pollen concentrations and temperature can also be observed in our data in Japan. Figure A1 displays the times series of average daily pollen counts in February–May and the average maximum temperature (Panel A) as well as the number of days above 30℃ (Panel B) in July and August in the *previous* summer, using station-year data from all the pollen monitoring stations (N= 120) during 2008–2019. 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 summer heat and the pollen counts in the following spring. For example, the year 2009 experienced a cold summer, and the pollen concentration in the spring of 2010 was relatively low. On the contrary, the year 2010 had quite a hot summer, and high pollen counts were observed in the spring of 2011.

Figure 1, mentioned in the introduction, formally establishes the associations between pollen counts and heat 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. The linear slope of 167.4 (t-stats= 11.2) in Panel A indicates that a 1 ℃ increase in the maximum temperature in the previous summer is associated with additional 167 grains/m^3 daily pollen counts in the following spring on average. 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 can be considerable. Similarly, the slope in Panel B is 23.7 (t-stats= 11.2), indicating that ten more hot days above 30℃ in the previous summer increase the daily pollen counts by 237 grains/m^3 in the following spring.

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

3. Data

We combine the daily airborne pollen counts with newly available administrative data that covers the entire accidents from ambulance records in the period 2008–2019 in Japan. To

our knowledge, we are the first to use this dataset for economic research. The details on data sources are provided in Appendix Section E.

3.1. Airborne Pollen

We obtain airborne pollen data from the Japanese Ministry of the Environment's pollen monitoring system (designated "Hanako-san"), which provides the 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 on measured pollen count is automatically published on the Ministry of the Environment 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 seasons in Japan. Thus, the cost of acquiring such information is nearly zero.

There is a total of 120 pollen monitoring stations located nationwide. Figure A4 displays the location of all monitoring stations as of 2019.[10] Each prefecture (out of 46) has two to three monitoring stations on average, placed in urban areas with high population densities and in mountainous regions that are the major source of pollen production (Wakamiya et al. 2019).[11] The number of pollen monitoring stations is extremely high, given the size of the country. For example, the US—which is 26 times as large as the size of Japan—has only 74 pollen monitoring stations nationwide, suggesting the density of pollen stations is *42 times* higher in Japan than in the US.

Since typical pollens in Japan can be distributed more than 100 km away and stay in the air for more than 12 hours, almost entire areas of Japan, even in sparsely forested cities, can be more or less contaminated by airborne pollens (Yamada et al. 2014).[12] Panel A of Figure A5 plots the cumulative distribution of the distance from the nearest pollen stations to the

[10] The number of pollen stations stays 120 since 2008, and thus our estimates are not affected by the entry and exit of monitors. The movement of monitoring stations is limited to a handful of stations and the distance of movement is very small.

[11] 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.

[12] National Allergy Bureau (NAB) suggests that pollen measurements are valid within a 20-mile (32 km) radius of each station, while Chalfin et al. (2019) use the criminal records from stations within 30 miles (48 km) of the city center.

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) suggested by Chalfin et al. (2019), 90.2% of all municipalities are within this threshold.

This 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 limit only 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 include a dichotomous variable that defines high pollen day.

Since the pollen emission from the Japanese cedar (the main plant of pollen production) 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.[13] We aggregate monitor readings to the daily level by summing across hourly observations to calculate the accumulated number of pollen grains in 24 hours. In addition, weather covariates from nearby weather stations are included in the same data. Specifically, hourly temperature, precipitation, and wind speed are recorded. Similarly, we aggregate these variables to the daily level.

3.2. Ambulance records

Our data on accidents come from the Fire and Disaster Management Agency (FDMA) of the Ministry of Internal Affairs and Communications. The data covers the universe of 2008–2019 ambulance calls that result in ambulance transportation to hospitals. The registration of all ambulance records to the online system of FDMA became mandatory in 2008. There are a total of 14.7 million accidents recorded throughout 2008–2019, with a yearly average of 1.2 million accidents (4.4 million in total with 368 thousand per year after limiting to pollen seasons only). See Figure A6 for the time series of the number of accidents.[14] The data provide detailed information on the level of individual accidents. We have information on location, the exact date and time of the ambulance calls, but also the type of accidents, the

[13] 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).

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

severity of injuries, place of occurrence, age, and gender of those involved in the accidents.

Two features of this dataset are particularly attractive for this study. The first unique feature is that we know the type of accidents: traffic accidents, work-related injuries, sports injuries, fire accidents, and others. Traffic accidents are particularly interesting as they are the second leading cause of accidental deaths (after asphyxia), with an average of over 4,000 and 700,000 annual fatalities and injuries from 2008–2019 (MHLW 2009; NPA 2022) in Japan with 127 million total population. Given the high base level of traffic fatalities and injuries, even a small change in fatal crash risk is highly relevant to social welfare. Furthermore, these car accidents can create a negative externality on those who do not suffer from seasonal allergies but get involved in the accidents. Similarly, work-related injuries are also worth mentioning as an increased risk of workplace injuries may imply that labor productivity, more broadly, could be undermined. Broten et al. (2019) document that workers injured on the job face a subsequent earnings penalty of 8% on average and 30% for those who are permanently disabled.

Another unique feature is that it includes information on the severity of injuries. This measure is expected to be very accurate as it is based on the initial assessment by the doctors who first see the injured person at the time of hospital admission. The severity measure ranges from death/fatal, serious, modest, to light, where "serious" accidents require more than three weeks of hospital admission and treatment; "modest" requires hospital admission but with less than three weeks, and "light" does not require hospital admission. One key advantage of ambulance records is that we can capture non-fatal but severe cases which are missed in vital statistics.

The geographical unit in ambulance records is an emergency response unit ("unit," hereafter), 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 US) across 46 prefectures (equivalent to states in the US) form 705 units. We aggregate the accident records to the unit-day level by summing across hourly observations within the units.[15]

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

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 sample spans from February to May (i.e., high pollen seasons only) for all prefectures except for Hokkaido, which spans from March–June during 2008–2019.

Table 1 presents summary statistics for our primary estimation sample, which consists of 970,309 unit-day observations. On average, there are 44.0 daily accidents per million people. Traffic accidents are the leading type of accident which, accounts for 35.8% of all accidents, followed by work-related injuries (4.2%), sports injuries (2.5%), and fire accidents (0.5%). The other accidents—not belonging to any of these types—account for over half of all accidents (57.0%).[16] Traffic accidents and other accidents together cover nearly 90%.

The mean daily concentration of airborne pollen is 1036 grains/m^3 (with a standard deviation of 2275). Figure A7 plots daily pollen counts for five selected locations from the north to south of Japan, demonstrating substantial variations in pollen concentration across spaces and time. Since pollen counts are rightly skewed, we take the log of pollen counts as the main regressor throughout the paper unless otherwise mentioned. Panel A of Figure A8 displays the histogram of logged daily pollen counts during 2008–2019, 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).[17]

[16] 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 to major ones.

[17] 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.

We later show the results from the alternative specifications (level-level and log-log) 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) control 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. 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.

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 1mm, 1mm to 2mm, and more than 2mm). We also control 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, the temporal, seasonal, and geographic variation in daily pollen counts is 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 showing the main results, we start by providing evidence of a "first stage"—whether people are more likely to suffer from seasonal allergy symptoms on high pollen days, using data on both internet search activities (Google Trends) and social media posts (Twitter data). All detailed results in this subsection are 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, (3) leading brand names of allergy medications in Japan during 2016–2019 at the prefecture-day level (N= 21,551). See Table B1 for the complete list of search keywords. 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.[18]

Figure 2 shows 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. Daily pollen counts and search index 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 Google 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 2016–2019 Twitter data at the prefecture-day level.[19] 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 show that people similarly tend to tweet these keywords more on high pollen days.

One advantage of Twitter data over Google Trend data, while the sample is more skewed to younger cohorts, is that people tend to express the status of "feeling" in Tweets.

[18] 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 1st, 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.
[19] We assign prefecture based on the location at the time of the Tweet.

Thus, we additionally collect the number of Tweets related to sleep, namely, "having a hard time falling asleep" and "feeling sleepy," as clinical studies suggest that deteriorated sleep quality is one path through which pollen exposure worsens cognitive functioning (Craig et al. 2004; Santos et al. 2006). Figure B3 and Table B3 show that people seem to have more sleep-related issues on high pollen days. This "first stage" evidence reassures that people do suffer from typical seasonal allergy symptoms that could trigger accidents on high pollen days.

5.2. Basic results

Figure 3 displays the binscatter plots of the relationship between the logged average 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 accidents (Panel B), work-related injuries (Panel C), sports injuries (Panel D), fire accidents (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 flattering 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) shows that a 10% increase in pollen counts leads to an increase in the number of accidents by 0.0228 (0.228×0.1) per million people, which is precise and highly statistically significant (p-value<0.001, t-stats= 14.0). Columns (2)–(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 (4.2% share), the elevated 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 all accidents and traffic accidents—a leading type of accident (35.8% share)—from here on. We discuss the monetary values of pollen-induced accidents in Section 6, where we project the potential damages from climate change.

Figure C1 plots the estimates from non-parametric binned regression to examine dose-responses more flexibly. Specifically, logged daily pollen in an 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 the low concentrations of pollen—which are more frequent than higher concentrations—can have a meaningful impact on cognitive performance and hence the incidence of accidents. This concave dose-response function also

points to the large benefits of reducing pollen concentrations even for countries with a relatively lower pollen level than our setting.

Importantly, our estimates provide a very lower bound as our ambulance records do not include the accidents on both sides of severity distribution, i.e., minor cases and immediate deaths that did not even require ambulance transportation to hospitals. In addition, the severity is measured at the time of hospital admission, potentially leading to the underestimation of eventual deaths. For example, the number of work-related accidents leading to death/fatal in our ambulance records in 2019 is 392, while the corresponding number reported to the Ministry of Health, Labor and Welfare Labor (MHLW) under the labor law requirement is 845 (MHLW 2020), suggesting a sizable understate of even most serious cases.[20]

5.3. Robustness

Our results on the effect of pollen exposure 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 nearby three stations (columns 2–3), adding pollution covariates (column 4)[21], limiting the sample to the units within 48 km from pollen monitoring stations to reduce the measurement errors (column 5), and an unweighted 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 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 underestimate the effect of pollen exposure. The short-lived effect is not surprising because while pollen triggers an allergic reaction within minutes after entering SAR sufferers, its effects generally do not last

[20] Similarly, the number of work-related injuries, including *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).
[21] 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.

more than 4 to 8 hours (Skoner 2001).[22] 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 shows 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-log specification or Poisson pseudo-maximum likelihood (PPML) model to account for the count nature of the data.

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 average daily pollen counts and the number of daily emergency ambulance transportation due to cancer. We find no discernable pattern as expected, reassuring that our results are not driven by specific unobserved seasonal or regional patterns.[23]

Replication—. Traffic accidents are also recorded in police records, which cover the universe of traffic accidents that resulted in personal injury and were reported to the National Policy Agency between 2019–2020 (see Appendix Section D for details on data). Table D1 compares the mortality estimates from traffic accidents using both ambulance records (our primary sample) and police records. While the estimate of pollen concentrations from police records is slightly larger than that of ambulance records (p-value<0.01), they are not statistically distinguishable.[24] In any case, 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, strengthening the internal validity of our estimates.

[22] The short-lived effect of pollen exposure is consistent with the previous literature documenting the short-lived impacts of pollution exposure on health (e.g., Schlenker and Walker 2016), crimes (e.g., Herrnstadt and Muehlegger 2021), and productivity (e.g., Graff Zivin and Neidell 2012; Chang et al. 2016, 2019).
[23] The ambulance records include detailed diagnosis information (equivalent to ICD10) from 2015 on.
[24] 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 record, which only captures deaths at the time of hospital admissions.

5.4. Heterogeneity

Severity—. One unique feature of our data is that it includes the severity of injuries based on the doctors' assessment at admission. Figure 4 plots the estimates along with a 95 percent confidence interval for each severity level, separately for all accidents (Panel A) and traffic accidents (Panel B). Panel A suggests that while the estimates become smaller as the severity level increase, all the estimates, including death/fetal, are positive and statistically significant. For example, a 10% increase in pollen counts leads to 5.6 (= 0.0037×0.1×127 million people×120 days in pollen season) additional accidental deaths per year. Panel B for traffic accidents shows similar patterns.

Other heterogeneity—. The ambulance records also include other characteristics of the accidents and the people involved. Using all accident samples, Figure 5 explores the heterogeneous treatment effect other than severity.[25] Panels A and B explore the heterogeneity by demographics, namely, age and gender. Overall, we find statistically significant effects in all age groups and both gender. Panel A indicates that the effect is significantly larger for the elderly (>65) than any other age group. This result is somewhat surprising as the prevalence of seasonal allergy is higher for younger ages, but this result is in line with the elderly's higher vulnerability to environmental externalities such as heat-mortality (Carleton and Solomon 2016; Carleton et al. 2022), cold temperature-mortality (Cohen and Dechezleprêtre 2022), and pollution-mortality (Jia and Ku 2019; Barwick et al. 2019) relationships. Panel B indicates a larger effect for males relative to females, albeit no statistical difference. Panel C examines the heterogeneity by location of accident occurrence. Interestingly, the increased accidents are found even at home, indicating the difficulty in completely blocking outdoor pollens as they can stay on clothes and are easily brought indoors or simply reflects the lingering effect of outdoor pollen exposure.

Intriguingly, Panel D of Figure 5 shows that the effect is statistically larger on weekends than on weekdays, even though most people should have more discretion to remain indoors on weekends than on weekdays, as discretionary trips can be canceled or rescheduled. This result hints at limited short-run avoidance behaviors. We explore this point further in the next subsection.

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

5.5. Short-term avoidance behaviors

Since the size of pollens is relatively large (≈30 μm) compared to much smaller particulate like PM2.5, they are less likely to penetrate into houses. Thus, the temporal but low-cost and effective means to reduce pollen exposure is simply to stay indoors and limit 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:

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

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 variable, RHS) 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.

The magnitude of avoidance behaviors—. To investigate the magnitude of avoidance behaviors $\left(\frac{\partial Avoid}{\partial Pollen}\right)$ in our context, we use the geolocation data (called ‘Mobile Spatial Statistics’ or MSS) provided by NTT Docomo, Inc., Japan’s largest mobile phone carrier. Based on the location information of 78 million users of NTT Docomo (out of a 127 million total population in Japan), MSS provides the population estimate at 500×500-meter mesh at an hourly level across Japan.[26] See Terada et al. (2013) for detailed procedures for

[26] 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, researchers can identify “home” locations as the most frequent locations of geographically contiguous stays (Miyauchi et al. 2021) and measure whether she/he

constructing population estimates. While physical mobility data has received huge attention in 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 to environmental stressors (see Burk et al. 2022). As in the other studies on physical movement, we cannot distinguish two possibilities for staying indoors: people are simply extremely sick and have to stay home or display some form of avoidance on high pollen days.

Our dataset on mobility measures is constructed as follows. First, for each municipality, we pick a mesh with the largest number of establishments in the service industry (e.g., accommodation, restaurants, and entertainment) from the 2016 Economic Census (MIC 2019).[27] We choose the service industry to 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 meshes to NTT Docomo, Inc, which returns the estimated population at each mesh from February–May 2014–2019. Third, we collapse the estimated population at the unit level by taking the average of all municipalities in the unit. Finally, we merge pollen data at the unit-date level.

Figure 6 displays the binscatter plots of the relationship between the logged pollen counts and the logged estimated population staying outside at 2 pm, as the daily population in commercial areas tends to peak around 2 pm (Seike et al. 2015).[28] Panel A shows no clear relationship between pollen counts and daytime 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

goes out from home, and their frequencies and distances. The downside 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 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 estimated population in a given area. Since the main objective of this paper is to provide the first nationally representative estimates on the effects of pollen exposure on accidents and corresponding avoidance behaviors, we choose the latter dataset in this study. Because of its sample representativeness, this dataset is widely used, especially in measuring people's mobility during the COVID-19 pandemic (e.g., Kondo 2021; Kuroda et al. 2022).

[27] Due to budgetary reasons, we limit to one mesh per municipality.

[28] We also examine the alternative ways of constructing outdoor mobility measures, specifically, the difference between daytime (2 pm) and nighttime (5 am) populations and the ratio of daytime to nighttime populations. The results are qualitatively similar (not shown) mainly because the nighttime population is relatively stable over time, and thus it does not provide much additional information after controlling unit FE. We choose logged daytime population as the main measure, as it can be interpreted as elasticity, and it is also easily comparable to the effect of pollen in logged form when we control it later.

that people seem to take some avoidance behaviors over the weekends.[29] However, as discussed below, the magnitude of avoidance is quite small.

Table 4 reports the estimate from the equation [1], where the outcome is logged number of populations outside. 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 elasticity of the number of populations outside 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 populations staying outside. Table 4 also reports the estimates on four indicators for rainfall (base: no rainfall) for comparison.[30] The estimated population staying outside decreases as rain intensity increases, suggesting that our population measure adequately captures people's decision-making about going outside. For example, the estimates from column (3) indicate that the rainfall between 1 mm and 2 mm reduces the population staying outside 9.9 times more than a 1% increase in pollen counts.

Finally, as we find a much larger effect of pollen on accidents for the elderly than non-elderly in Figure 5, columns (4)–(7) of Table 4 repeat the same exercise separately for the non-elderly and elderly (>60). Columns (4) and (5) show that the non-elderly display similar patterns as the overall population; there is no effect over the weekdays but a small but statistically significant negative estimate of –0.0029 (p-value<0.01) on weekends. However, for the elderly, we do not find any indication of avoidance behaviors either over the weekdays or weekends in columns (6) and (7). This result might imply that the higher vulnerability of the elderly to environmental stressors (such as temperature and pollution) documented elsewhere can be partially explained by their lack of risk awareness, leading to limited avoidance behaviors.

Controlling avoidance behaviors—. Following the spirit of previous studies on avoidance behaviors for air pollution (e.g., Neidell 2009), we quantify the contribution of avoidance behavior by comparing the estimates of an equation [1] with and without controlling for the avoidance behaviors *proxied* by the logged number of population staying

[29] This result is consistent with Chalfin et al. (2019) and Kuroda (2022) documenting fewer outdoors people (proxied by the public's usage of bicycle rental services) and a decrease in consumption using scanner data in Japan on high pollen days.

[30] See Table A2 for the estimates of other weather covariates with expected signs: while the estimated population staying outside increases as temperature rises, it decreases as the average wind speed and duration of darkness increases.

outside.[31] However, we should interpret this result with considerable caution as the number of people outside is indeed endogenous.

For this exercise, we merge our accidents-pollen sample with the geolocation data by unit-day to construct the subsample between Feb–May 2014–2019. Column (1) of Table 5 replicates similar results as column (1) of Table 2, using this smaller sample. Column (2) adds the logged number of the population staying outside to column (1) in order to control the impact of avoidance behaviors. Notably, the estimate of the population staying outside is positive and highly statistically significant (p-value<0.05), suggesting that simply curtailing outside activities can be an effective means to reduce the risk of accidents.[32] It is also again reassuring that our population measure well captures people's decisions to go outside. However, the estimate of pollen on accidents in column (2) without avoidance control is almost identical to the one in column (1) without such control (0.2163 vs. 0.2159), suggesting that our measure of avoidance plays a minor role here. This result is consistent with the very limited avoidance behaviors documented above. Table C5 repeats this exercise separately for weekdays and weekends, but even for weekends, the estimates of pollen on accidents increase only by 0.04 (from 0.269 to 0.273) by controlling avoidance behaviors or as small as 1.4%.

To summarize, the "behavioral" effect from column (1) of Table 5 is almost identical to the "biological" effect from column (2) because the effect of avoidance $\left(\frac{\partial Accidents}{\partial Avoid}\frac{\partial Avoid}{\partial Pollen}\right)$ is close to zero, at least in this setting. Interestingly, the first term of the avoidance effect $\left(\frac{\partial Accidents}{\partial Avoid}\right)$—the marginal return from reducing outside activities on accidents—is indeed negative and highly statistically significant, as shown in column (2). Thus, the lack of the effect of avoidance is mainly driven by the second term—negligible behavioral responses to pollen $\left(\frac{\partial Avoid}{\partial Pollen} \approx 0\right)$. This finding sharply contrasts with the case of air pollution, where Neidell (2009), for example, shows that the "reduced form" effect that accounts for avoidance behaviors is 40% and 160% smaller for the elderly and children than the pure "biological" effect.

Of course, considerable caution is necessary to interpret this result as we only capture one type of avoidance behavior—refraining from going outside. For example, there are other

[31] Similarly, Neidell (2009) compares the estimates with and without including avoidance behaviors (proxied by smog alerts) when estimating the relationship between ozone and respiratory-related hospital admissions.

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

potentially cost-effective methods, such as wearing particulate-filtering masks and glasses and avoiding wearing the type of clothes that easily attach pollen (e.g., woolen coats).

Policy implications—. At least in our context, people's behavioral responses to an elevated pollen level seem small. However, it is unlikely that this low response is driven by the sheer lack of awareness by pollen sufferers, as evident from an analysis of Google Trends and Twitter data. Suppose the behavioral response term $\frac{\partial Avoid}{\partial Pollen}$ in equation [2], which is 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 LHS is nearly zero, and the second component of the RHS variable—"availability of information"—seems quite positive (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 policy-wise important because if information access is lacking, the government should target disseminating pollen information more widely. On the other hand, if access to information is sufficient, but awareness of risk is lacking, we should find more effective ways to raise awareness of the risk ("salience") and encourage more widespread behavioral change. For example, the public information campaigns such as "pollen alert"—to encourage curtailing outdoor activities or recommend using public transportation on high pollen days—can be a possibly low-cost and effective tool to reduce pollen-induced accidents. 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).

Of course, unlike "ex-post" government interventions like pollen alerts, the "ex-ante" intervention to reduce the pollen concentration could be more cost-effective. Such interventions might include trimming pollen-emitting trees and replanting newly invented less pollen-emitting trees. Such a process may take time, however, thus ex-post intervention like pollen warning 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 take time. For example, recent medications for seasonal allergies cause less drowsiness and reduce the risk of drowsy

driving. See Table A1 for the list of medications for seasonal allergies released from 1994 to 2017 in Japan, demonstrating that more recent medications tend to have no specific mention of driving, unlike past medications that mention either "Driving not allowed" or "Careful driving required."[33] People may also engage in defensive spending (e.g., buying air purifiers) over a longer span. Furthermore, unlike short-run physiological acclimatization, *behavioral* acclimatization may require more time to take effect (Graff Zivin and Neidell 2014).

We examine 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 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 fall over time. We empirically test this by dividing the 12-year sample period (2008–2019) into three intervals of four years. Panel F of Figure 5 shows that while pollen-accident sensitivity becomes slightly smaller in the last period than in the earlier periods, the magnitude of the decline is marginal, and none of the estimates in the three intervals are statistically distinguishable from each other.[34]

Finally, we divide 705 units into quantiles by the mean of pollen counts during 2008–2019 to investigate whether people who live in the higher pollen regions, on average, experience smaller impacts of pollen concentrations than those who live in the lower pollen regions through (longer-term) adaptation. Figure C5 shows that the estimates are pretty similar across quantiles, again indicating limited longer-term adaptive potential. Taken together, we fail to find strong evidence of medium-term adaptation to the destructive impact of pollen exposure, at least in this setting.

6. 'Projecting' damages from climate change

This section combines the estimates from Section 5 on the effect of pollen exposure on accidents 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

[33] 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 echoes these findings.
[34] 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 see obvious declining patterns over the year.

changes in the number of pollen-induced accidents from climate change.[35]

Table 6 summarizes the damages projected from different climate change scenarios. We start with the 'business as usual' scenario (RCP 8.5), which predicts that the summer temperature in Japan is expected to increase by 4.2℃ in the years 2071–2100 (MEXT and JMA 2020). We calculate the number of additional pollen-induced accidents associated with this temperature change as follows. From the relationship between the summer temperature and pollen counts (Panel A of Figure 1), this increase in temperature leads to additional daily pollen counts by 703 (= 167.4×4.2) grains/m^3, which corresponds to a 0.518 increase in logged pollen counts from the mean of 1036 grains/m^3. We multiply the baseline estimates from Panel A of Figure 4 for each severity level with 0.518, then by the 127.4 (million population), and further by 120 (days of typical pollen seasons) to calculate the additional annual accidents as reported in a row (1). Row (1) indicates that a 4.2℃ increase in the average summer temperature is expected to increase the pollen-induced death/fatal, serious, modest, and light accidents by 30, 212, 529, and 1015, summing to 1785 additional annual accidents.

Then, we convert these additional accidents into monetary terms by multiplying the resulting accident counts in a row (1) with the average accident costs from Bünnings and Schiele (2021) as reported in a row (2): $3.2 million (death/fatal), $365 thousand (serious), and $38 thousand (both modest and light).[36] Row (3) indicates that pollen-induced death/fatal, serious, modest, and light accidents translate into $94.3, $77.4, $20.2, and $38.7 million, totaling an annual social cost of $231 million in a row (4). Interestingly, this is by far larger than $1.1 million—the current budget of Japan's Forestry Agency for the pollen reduction program (Forest Agency 2021).

The right side of Table 6 repeats the same exercise for the 'slowest warming' scenario (RCP2.6) with only a 1.3℃ increase in the average summer temperature, leading to a total social cost of $85 million. Thus, a measure that can reduce the level of global warming from business as usual to slowest would have at least an estimated annual cost savings potential of $146 million (or 1128 fewer accidents, including 19 deaths). Panel B of Table 6, using the

[35] 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.

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

number of days 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.

We note that this simple damage projection is still likely to yield a conservative estimate since (i) we do not take into account the prolonged pollen season due to the hot summer, (ii) we only consider roughly four months of high pollen season (see Figure A2 of pollen calendar), (iii) we miss the accidents at both sides of severity distribution (minor cases as well as immediate deaths) that did not even require ambulance transportation to hospitals as well as eventual deaths, and (iv) we use relatively conservative values of a statistical life (Bünnings and Schiele 2021) than commonly used one.[37]

7. Conclusion

We provide, to our knowledge, the first assessment of the impact of pollen on the number of accidents using a seasonal and temporal variation of pollen concentrations in Japan. We find that exposure to elevated pollen increases all types of accidents, ranging from major to minor ones, including deaths, using the universe of ambulance records during 2008–2019. Our results are consistent with long-standing, clinical-based literature documenting adverse cognitive impacts of pollen exposure, the long-run implications of which have not previously been tested in real-world environments except for children's academic performance. Moreover, as we find broadly uniform pollen effects across a range of observed demographics, locations, calendar months, and limited evidence of changes in the treatment effects, at least within our limited sample period, the underlying mechanism linking pollen exposure with accidents is perhaps generalizable across contexts and individuals.

Projecting damages from end-of-century climate change, we find that the business-as-usual scenarios with an expected rise in the summer temperature by 4.2℃ lead to annual 1785 additional pollen-induced accidents. With the relatively conservative average accident costs, the social cost of such extra accidents is $231 million per year at a minimum.

Our analysis of internet search activities and social media posts for pollen-related topics suggests that people seem to have a good sense of daily pollen levels and the availability of health-protection measures. At the same time, limited avoidance behaviors from geolocation data imply that people are imperfectly aware of or underestimate the cognitive risk of pollen

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

exposure. Thus, the current situation that relies on self-protection to mitigate pollen exposure risk may only have modest benefits. Government efforts to raise awareness of such risk and promote more widespread behavioral change might be warranted.

Finally, it is important to reiterate that the estimated social cost we uncover might reflect only the tip of the iceberg of the potentially enormous social cost associated with pollen load. While we remain agnostic on the underlying mechanisms, to the extent that exposure to pollen impairs cognitive function, such as lack of concentration and longer response time, any daily human activities that require normal cognitive performance and decision-making ability can be similarly affected. Quantifying such potential damages is an avenue toward understanding the full costs of pollen concentration.

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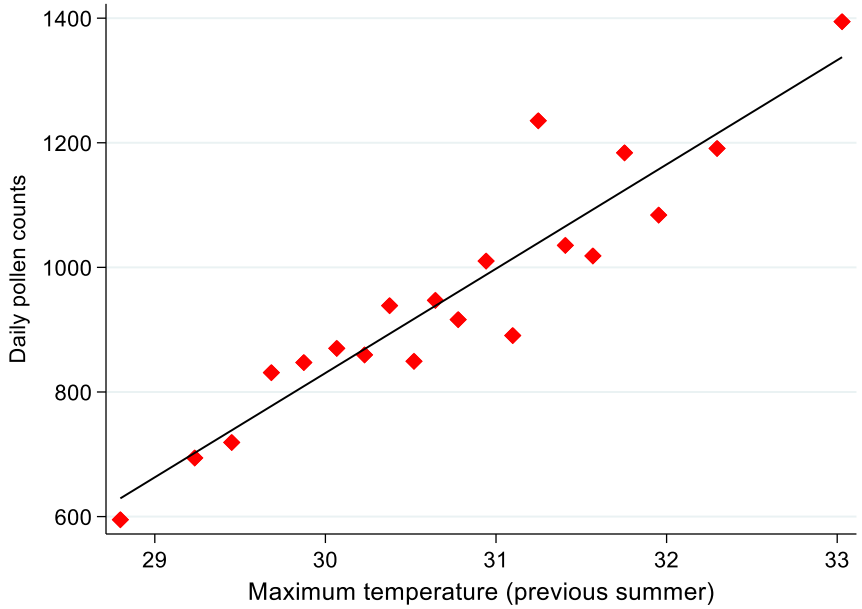
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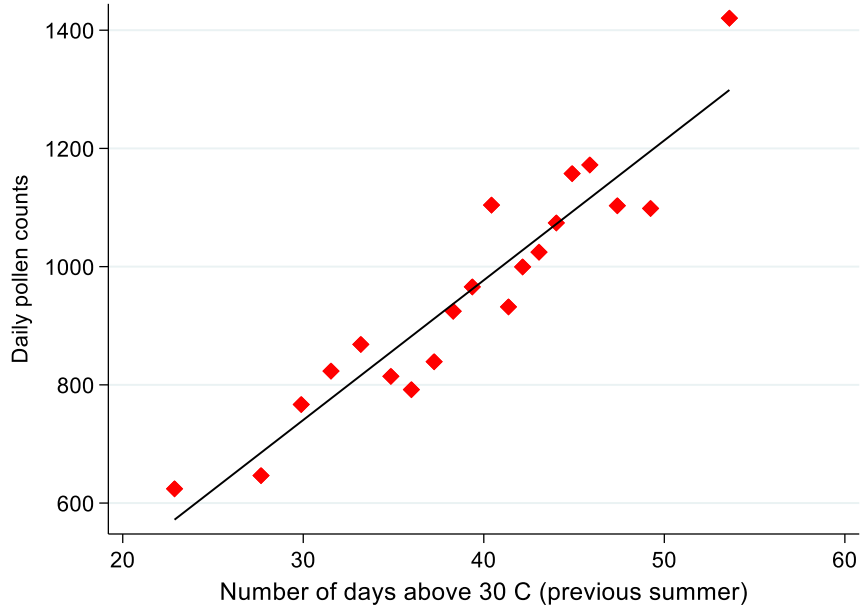
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Figure 1—Pollen counts and heat in the previous summer

A. Maximum temperature in the previous year

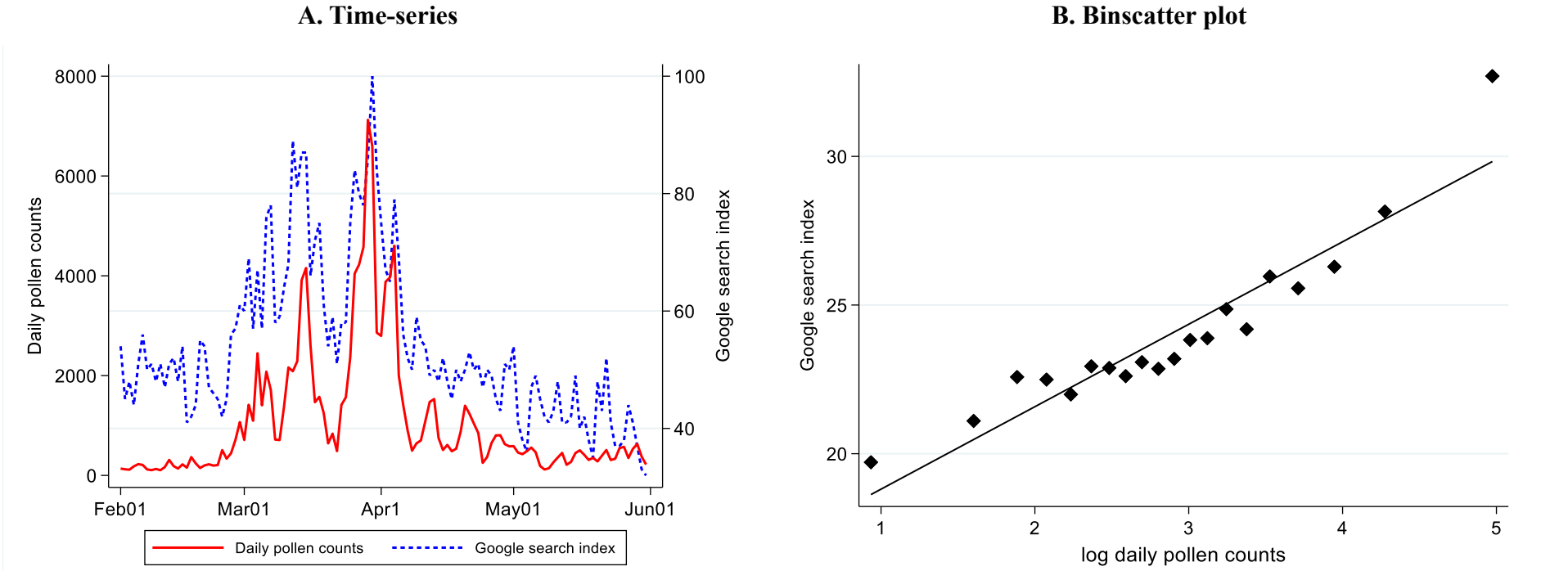


B. Number of days above 30℃ in the previous year



Notes: The graphs display the binscatter plots of the relationship between average (24-hour cumulative) daily pollen counts (grains/m^3) from February to May and the average maximum temperature (in ℃) in Panel A and the number of days above 30℃ in Panel B in July and August in the previous summer after controlling for pollen monitoring station FE. The sample consists of station-year (N = 1440) from all the pollen monitoring stations (N=120) during 2008–2019 (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 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 more hot days above 30℃ in the previous summer increase the daily pollen counts by 237 grains/m^3. The mean and median of daily pollen counts from February to May during 2008–2019 at 120 monitoring stations are 955.6 and 712.5 grains/$m^{3,}$ respectively.

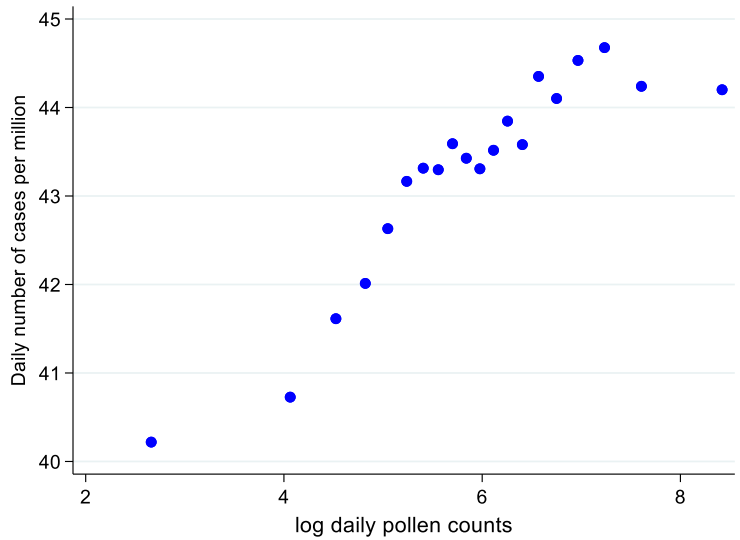
Figure 2—Pollen and symptom-related Google search index



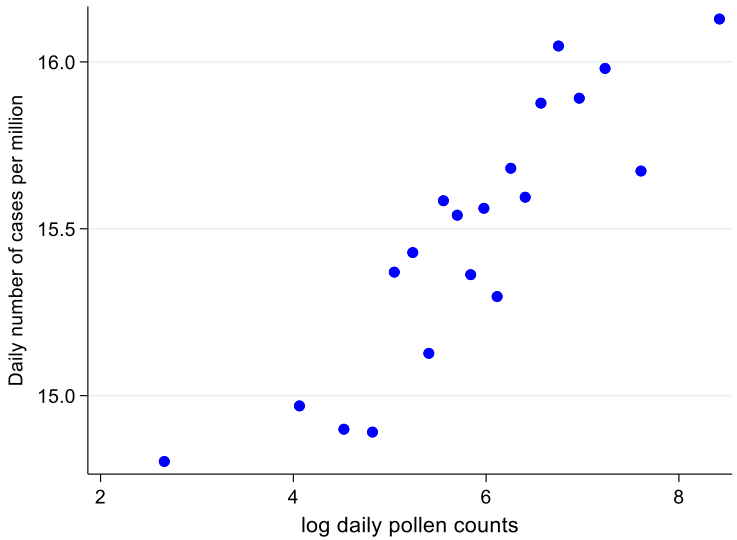
Notes: Panel A shows the time series patterns of the average daily pollen counts (grains/m^3) and Google search index for symptom-related keywords in 2018 at the country level. The symptom-related keywords are "runny nose," "nasal congestion," "sneeze," and "itchy eyes." June is omitted as only four 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—Pollen and the number of accidents

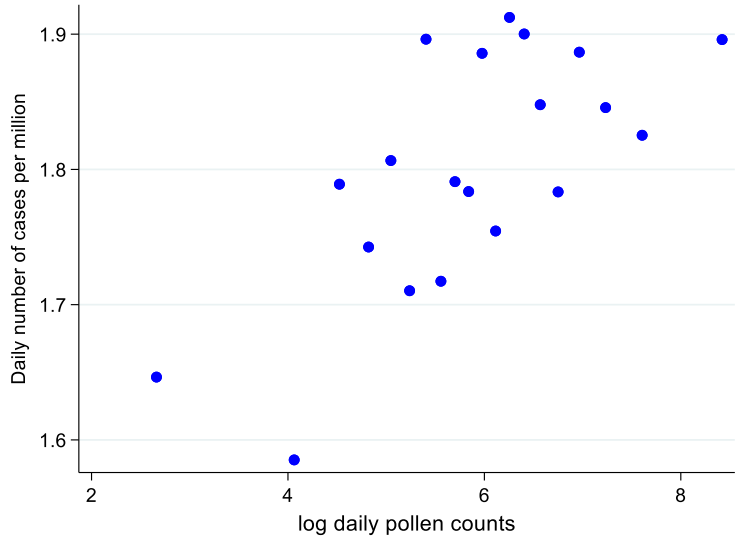
A. All accidents



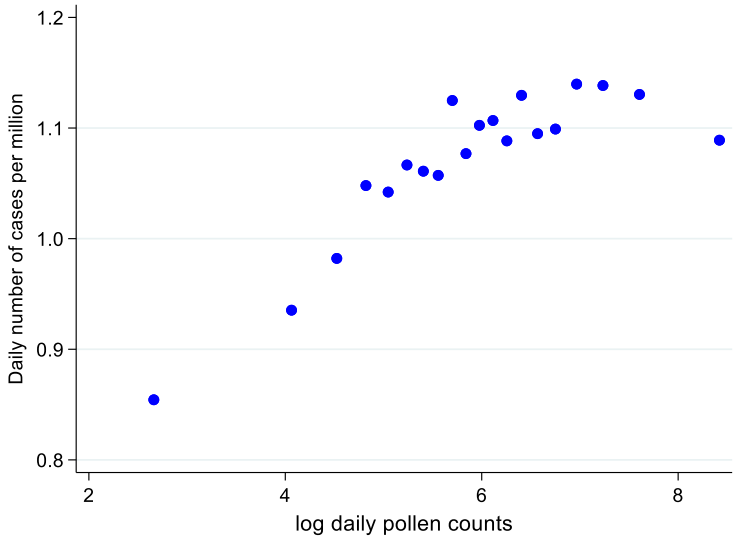
B. Traffic accidents

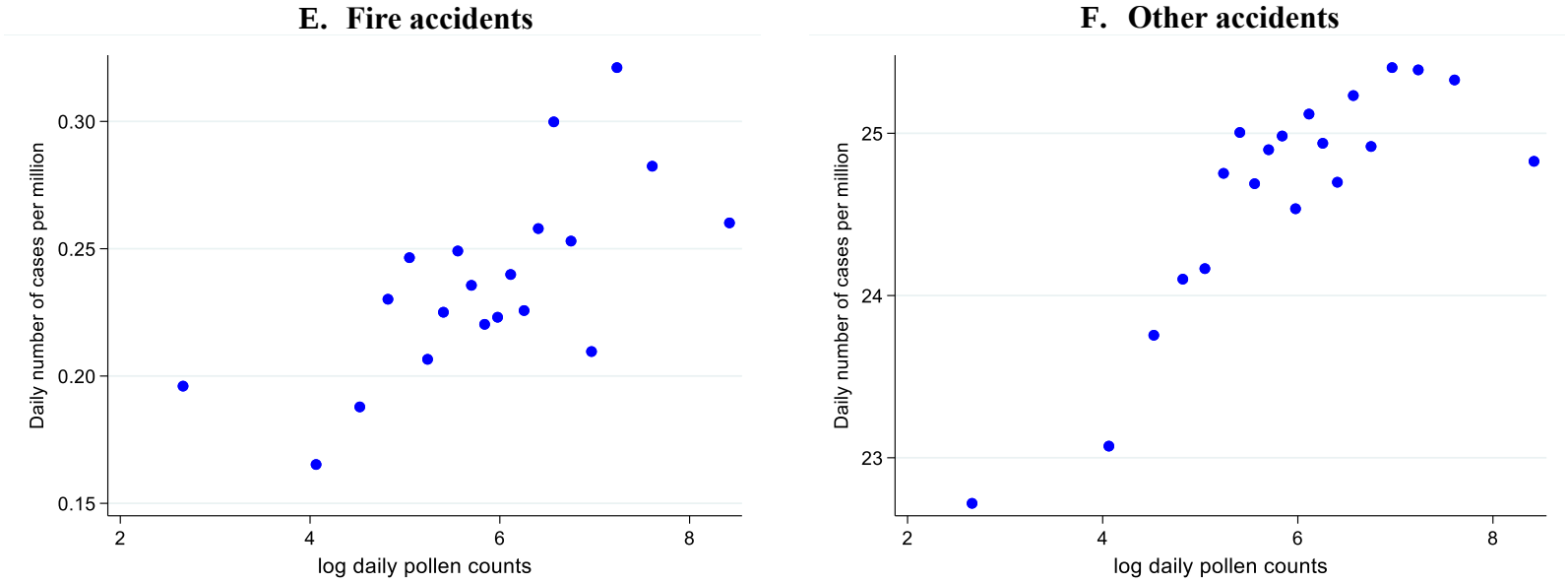


C. Work-related injuries



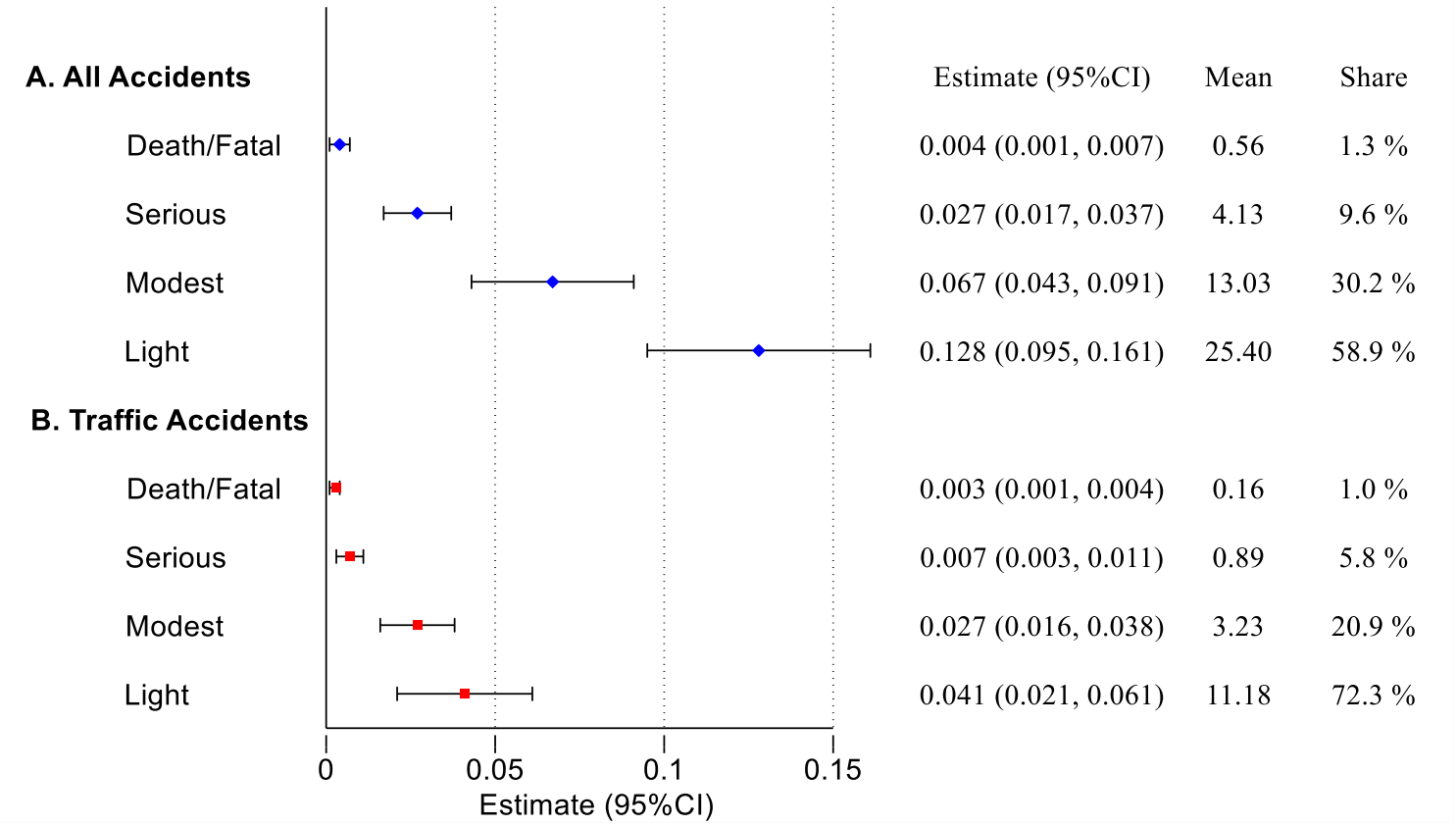
D. Sports injuries





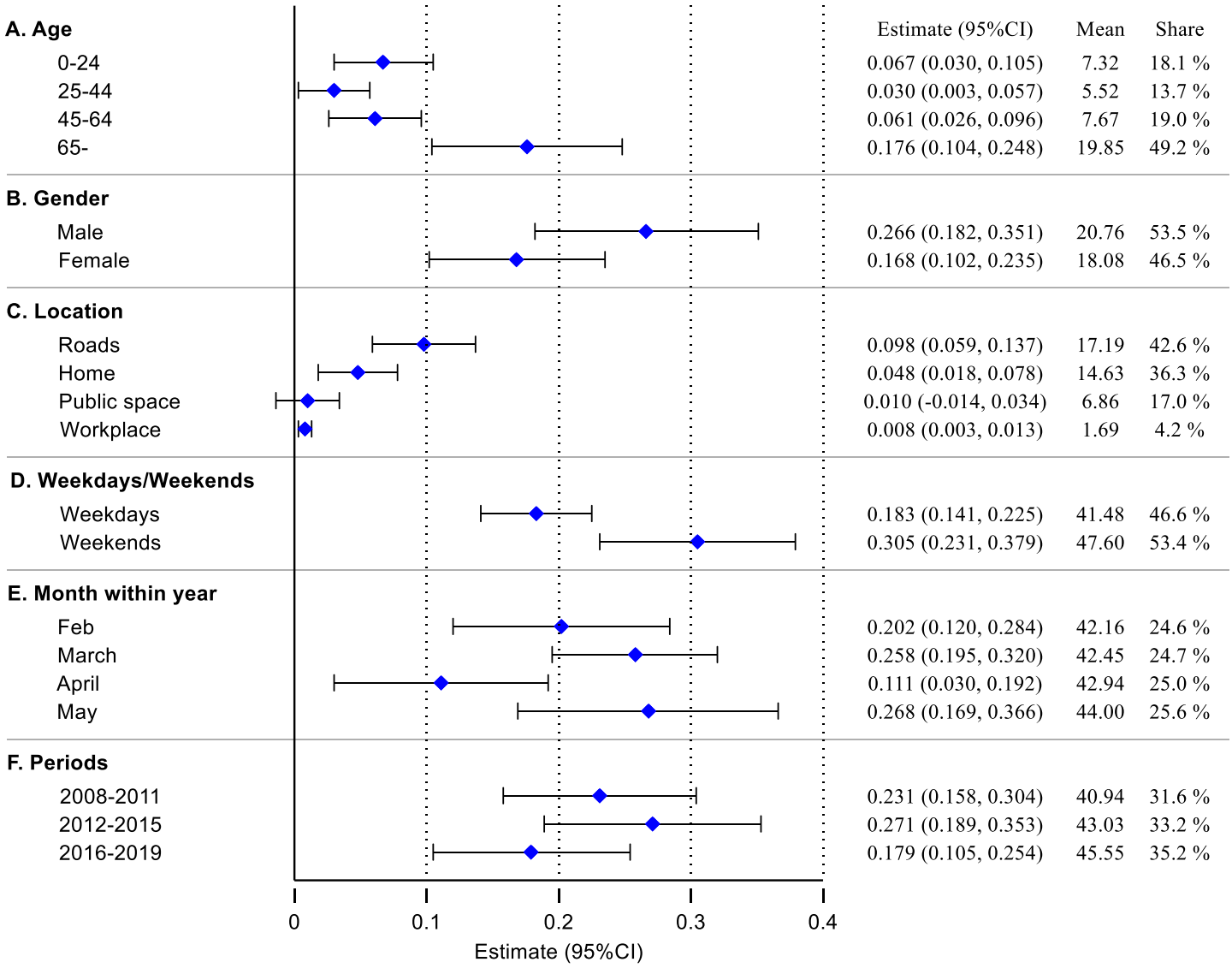
Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N = 970,309). There are 705 units in total. The graphs display the binscatter plots of the relationship between the logged daily pollen count (grains/m^3) and the number of daily cases per million people for all accidents in Panel A and each type of accident in Panels B–F traffic accidents (Panel B), work-related injuries (Panel C), sports injuries (Panel D), fire accidents (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 35.8%, 4.2%, 2.5%, 0.6%, and 57.0% respectively.

Figure 4—Treatment effects by severity



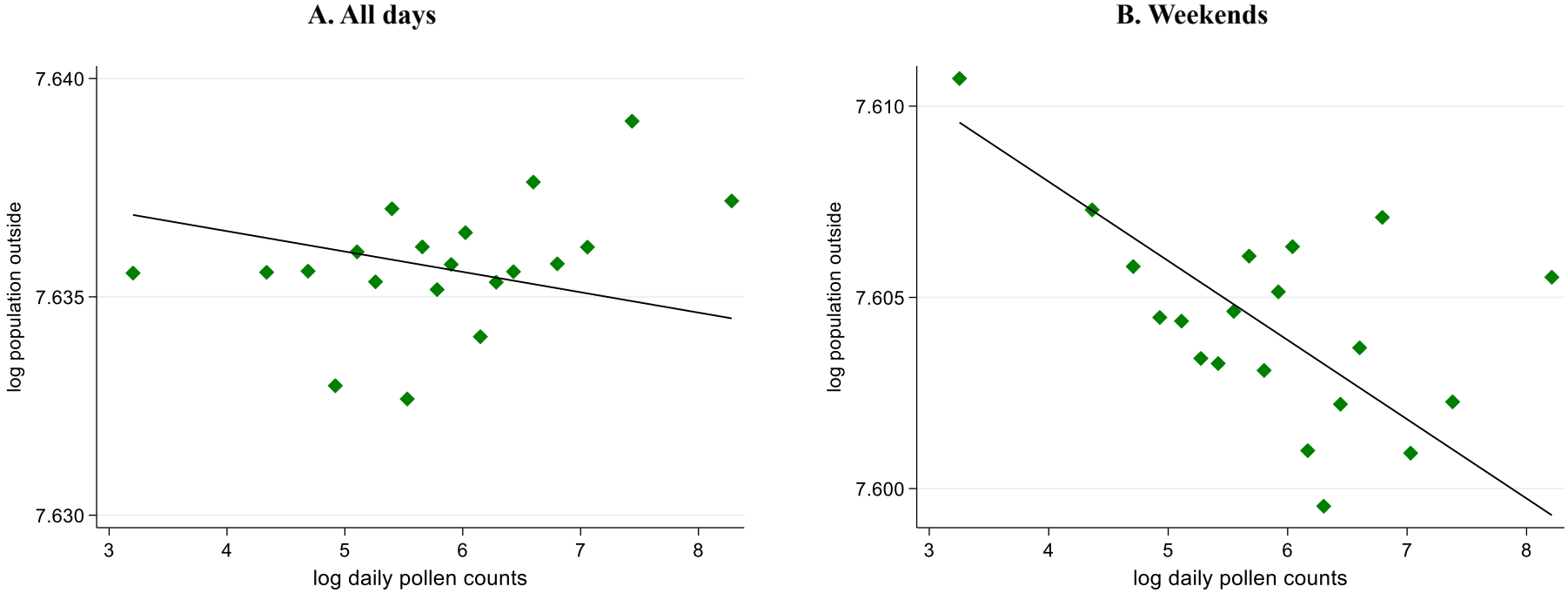
Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95 percent confidence interval of treatment effects of logged daily pollen count from equation [1]. The standard errors 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 admissions. "Serious" accidents are defined as the level of injuries requiring more than three weeks of hospital admissions and treatment; "modest" requires hospital admission, but the length of stay should be less than three weeks, and "light" does not require hospital admissions. 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 share of traffic accidents (Panel B) among all accidents is 35.8%. Estimates are weighted by the population in each unit. The mean reported second to the far right is the number of daily cases per million people. The share reported on the far right is summed to 100 percent within the panels.

Figure 5—Other heterogeneous treatment effects (All accidents)



Notes: The sample comes from 2008–2019 ambulance records, 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 percent 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. 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 reported second to the far right is the number of daily cases per million people. The share reported on the far right is summed to 100 percent within the panels.

Figure 6—Pollen and avoidance behaviors



Notes: The sample comes from 2014–2019 cell-phone location data, and the level of observation is 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 staying outside 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	Obs	Mean	Std. dev.	Min	Max
A. Outcomes (per million people per day)					
All accidents	970,309	43.21	67.80	0	5,091
Type: Traffic accidents	970,309	15.48	38.37	0	5,091
Type: Work-related injuries	970,309	1.80	11.74	0	1,367
Type: Sports injuries	970,309	1.07	7.77	0	1,195
Type: Fire accidents	970,309	0.24	5.44	0	2,612
Type: Other accidents	970,309	24.63	46.05	0	2,447
Severity: Death/Fatal	970,309	0.56	6.58	0	943
Severity: Serious	970,309	4.13	18.20	0	1,572
Severity: Modest	970,309	13.03	32.04	0	1,958
Severity: Light	970,309	25.40	46.66	0	4,570
Ages: 0-24	970,309	7.36	21.08	0	2,112
Ages: 25-44	970,309	5.55	19.04	0	2,186
Ages: 45-64	970,309	7.72	23.20	0	2,637
Ages: 65-	970,309	19.93	40.63	0	2,695
Gender: Male	970,309	20.88	41.88	0	4,769
Gender: Female	970,309	18.15	37.77	0	2,366
Location: Roads	970,309	1.94	4.15	0	198
Location: Home	970,309	1.47	3.06	0	89
Location: Public space	970,309	0.72	1.79	0	51
Location: Workplace	970,309	0.15	0.48	0	58
B. Regressors (per day)					
Pollen count (grains/m^3)	970,309	1036.1	2275.2	0	55,104
Log (Pollen count)	970,309	5.86	1.54	0	10.91
Precipitation (mm)	970,309	0.2	0.4	0	9.6
Average temperature (℃)	970,309	11.5	6.2	-11	28
Average wind speed (m/s)	970,309	2.7	1.4	0	15.7
Darkness (hours)	970,309	10.4	1.3	7	13
SO_2 (ppb)	852,948	2.0	2.9	0	521
NO_2 (ppb)	846,659	10.5	7.9	0	88
CO (0.1ppm)	848,798	3.7	1.6	0	61
OX (ppb)	850,847	37.7	11.3	0	120
PM10 (μg/m3)	850,577	19.0	10.7	0	299

Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day. There are 705 units in total. 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	Fire accidents	Other accidents
	(1)	(2)	(3)	(4)	(5)	(6)
log (pollen)	0.228***	0.079***	0.012***	0.007*	0.006***	0.125***
	(0.017)	(0.012)	(0.003)	(0.003)	(0.002)	(0.015)
R-squared	0.47	0.25	0.06	0.08	0.00	0.38
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	43.21	15.48	1.80	1.07	0.24	24.63
Share	*100%*	*35.8%*	*4.2%*	*2.5%*	*0.6%*	*57.0%*
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 comes from 2008–2019 ambulance records, 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 shares of traffic accidents, work-related injuries, sports injuries, fire accidents, and other accidents are 35.8%, 4.2%, 2.5%, 0.6%, and 57.0%, respectively. 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)	0.228***	0.231***	0.246***	0.219***	0.226***	0.401***	0.231***	0.259***	0.212***
	(0.020)	(0.021)	(0.022)	(0.022)	(0.020)	(0.066)	(0.037)	(0.052)	(0.035)
R-squared	0.47	0.47	0.47	0.47	0.49	0.33	0.63	0.71	0.86
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***	0.089***	0.072***	0.077***	0.138***	0.086***	0.110***	0.125***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.037)	(0.019)	(0.026)	(0.020)
R-squared	0.25	0.25	0.25	0.24	0.26	0.12	0.39	0.49	0.70
N	970,309	970,309	962,255	814,578	872,227	970,309	961,901	953,522	147,066

Notes: The sample comes from 2008–2019 ambulance records, 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 in Panel B among all accidents is 35.8%. 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 nearby three stations as the main regressor. Column (3) drops zero pollen counts (0.83%) and takes log without adding 1. Column (4) adds air pollution covariates (SO2, NO2, CO, OX, PM10) for 2009 April-2019 April when such data are available. Column (5) restricts the sample to the units within 48 km of monitoring stations. Column (6) is an unweighted 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 week		C. By age			
				Non-elderly		Elderly (≥ 60)	
		Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log (pollen)	-0.0005	0.0000	-0.0021***	-0.0007	-0.0029***	0.0005	-0.0013
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0006)	(0.0009)
Rain (base: no rain)							
<1 mm	-0.0061***	-0.0059***	-0.0047**	-0.0050***	-0.0032	-0.0121***	-0.0111***
	(0.0013)	(0.0011)	(0.0019)	(0.0011)	(0.0020)	(0.0016)	(0.0027)
1 mm≤ & < 2 mm	-0.0167***	-0.0144***	-0.0208***	-0.0089***	-0.0170**	-0.0283***	-0.0365***
	(0.0035)	(0.0024)	(0.0080)	(0.0020)	(0.0077)	(0.0040)	(0.0122)
≥ 2 mm	-0.0167***	-0.0150***	-0.0249***	-0.0095**	-0.0162*	-0.0334***	-0.0466***
	(0.0045)	(0.0041)	(0.0082)	(0.0042)	(0.0086)	(0.0057)	(0.0095)
R-squared	0.98	0.99	0.99	0.97	0.97	0.97	0.97
N	478,853	343,454	135,399	475,883	474,635	474,635	474,635
Pref FE	X	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X	X
Month-year FE	X	X	X	X	X	X	X
Month-prefecture FE	X	X	X	X	X	X	X

Notes: The sample comes from 2014–2019 (Feb-May) cell-phone location data, 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 outcome is the logged daily number of people staying outside 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 A2 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 people outside)		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 comes from 2014–2019 ambulance records 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 is 35.8%. 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) just add the logged number of people staying outside at 2 pm 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

	Under RCP8.5 ('business as usual')				Under RCP2.6 ('slowest warming')			
A. Maximum temperature	+4.2 ℃				+1.3 ℃			
Severity level	*Death/fatal*	*Serious*	*Modest*	*Light*	*Death/fatal*	*Serious*	*Modest*	*Light*
(1) Increases in accidents per year	29.5	211.8	529.2	1,014.8	10.9	78.0	194.8	373.5
(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)	94.33	77.40	20.20	38.74	34.72	28.49	7.44	14.26
(4) Total social cost per year (million USD)	230.7				84.9			
B. Number of days above 30℃	+48.6 days				+13.1 days			
Severity level	*Death/fatal*	*Serious*	*Modest*	*Light*	*Death/fatal*	*Serious*	*Modest*	*Light*
(1) Increases in accidents per year	42.6	305.7	763.7	1,464.5	14.9	107.2	267.8	513.5
(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)	136.13	111.71	29.15	55.91	47.73	39.17	10.22	19.60
(4) Total social cost per year (million USD)	332.9				116.7			

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 above 30℃ (Panel B of Figure 1). The total social cost per year in a row (4) for Panel A is calculated as follows. Taking RCP8.5 as an example (on the left), the increase in average temperature by 4.2℃ leads to an increase in the daily pollen counts by 703.1 (=167.4 × 4.2), where 167.4 comes from Panel A of Figure 1. This leads to 0.518 increases in logged pollen counts from the mean (=*log*(1036+703.1)-*log*(1036)). Row (1) is the product of each severity level estimate from Table 4 and 0.518, then by 127.4, which is the average population (in millions) in Japan during 2008–2019, and finally by 120 days (Feb to May) of typical pollen seasons in Japan. The figures in row (2) come from Bünnings and Schiele (2021), 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, taking RCP8.5 as an example (on the left), the increase in the number of days above 30℃ 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 0.747 increases in logged pollen counts (=*log*(1036+1151.8)-*log*(1036)). The remaining steps for rows (3) and (4) are identical. The total social cost for RCP2.6 is calculated in the same way.

Online Appendix
(Not for Publication)

"Invisible Killer": Seasonal allergy and accidents

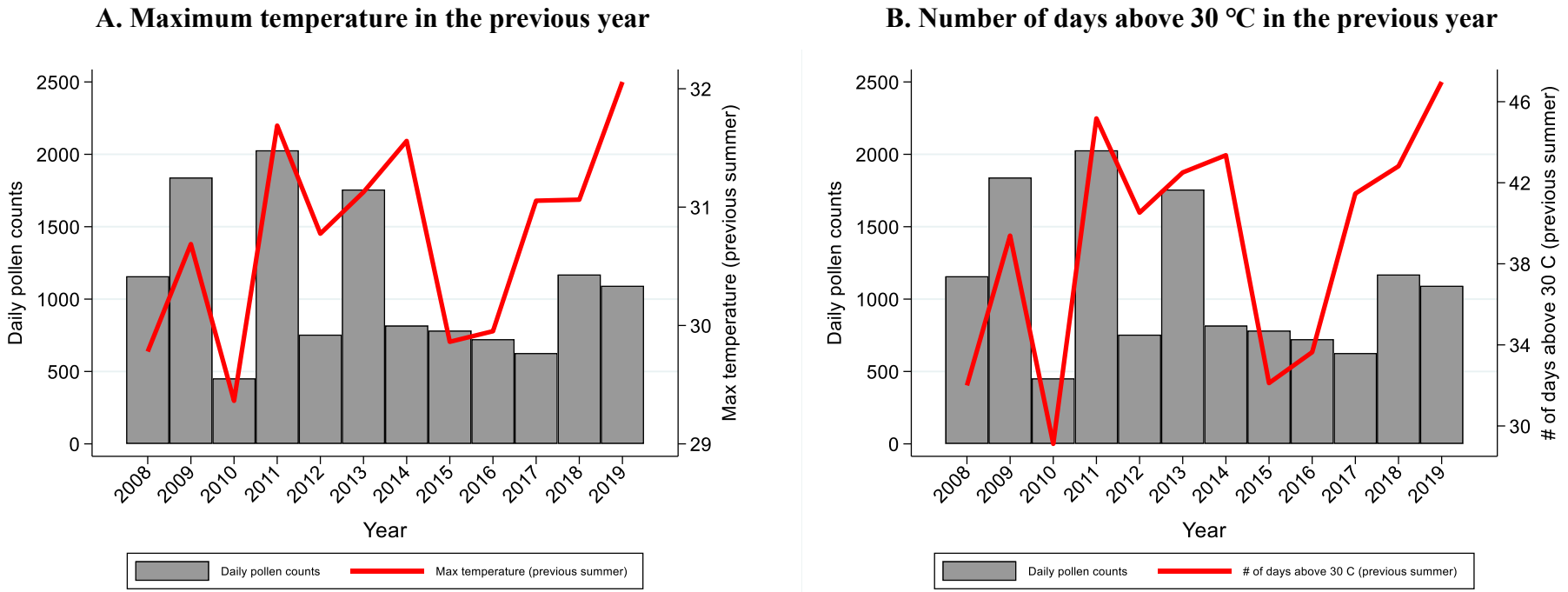
By Mika Akesaka, and Hitoshi Shigeoka

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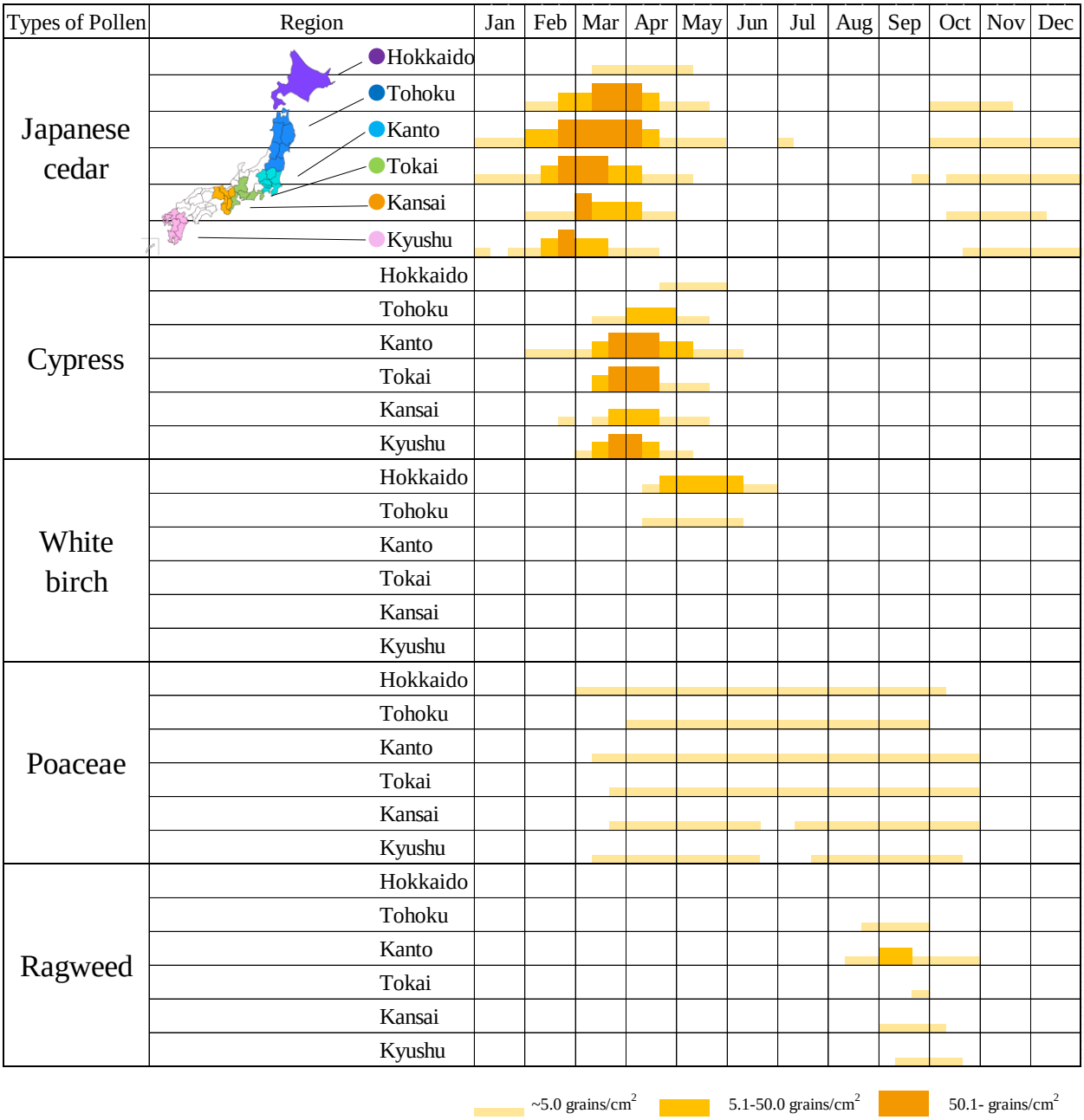
Appendix A: Additional Figures and Tables

Figure A1—Times series of pollen counts and maximum temperature in the previous year



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

Figure A2— Calendar of pollen season in Japan



Notes: The table 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, monitor 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: "Practical Guideline for the Management of Allergic Rhinitis in Japan," published by the Japan Society of Immunology, Allergology and Infection in Otorhinolaryngology.

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

A. Today's forecast



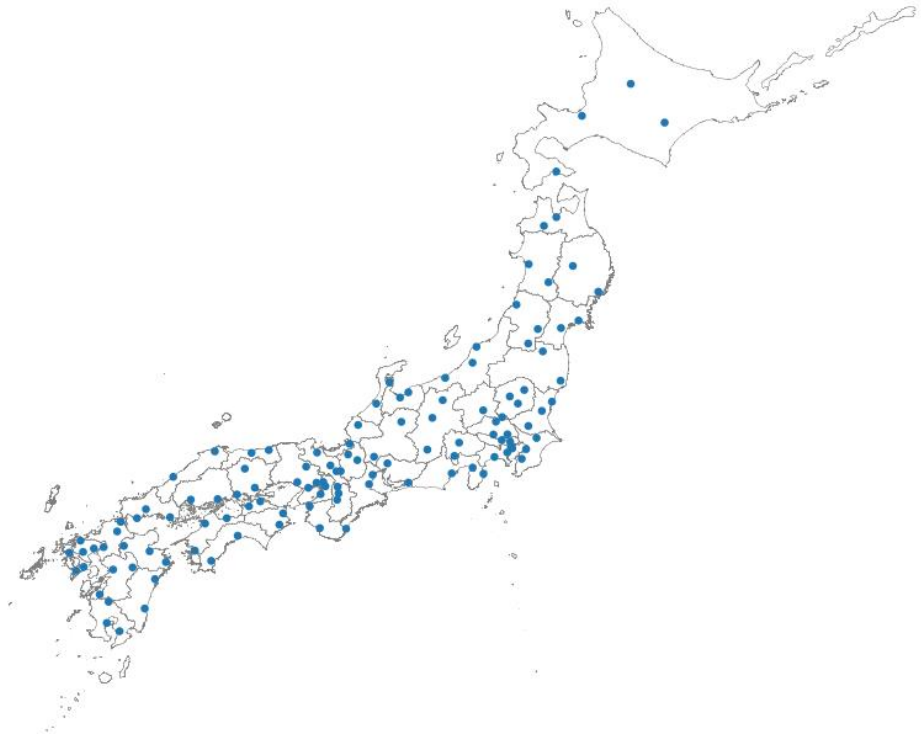
B. This week's forecast



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 at various locations in Japan.

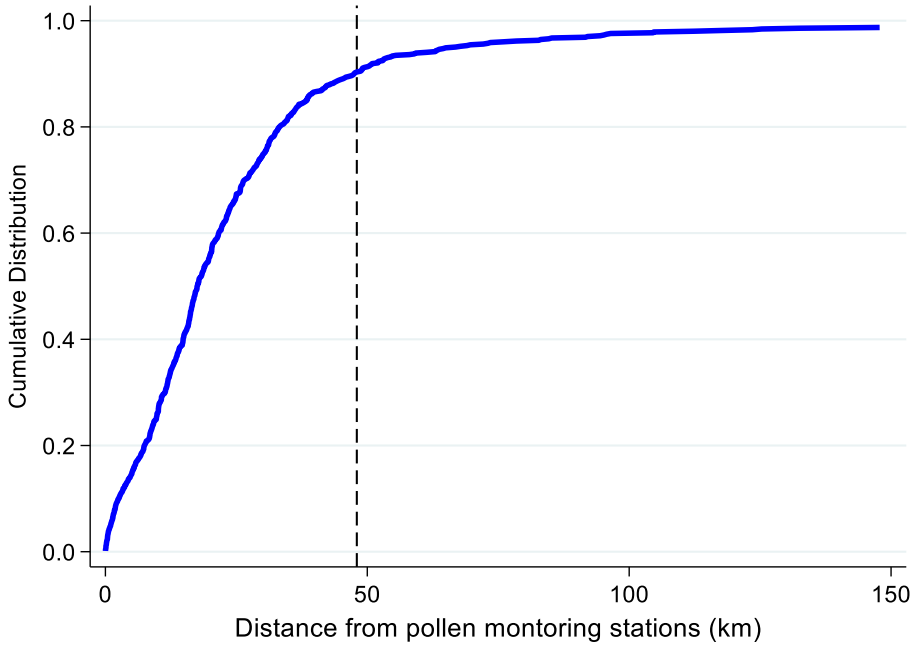
Sources: Japan Weather Association (https://tenki.jp/)

Figure A4—Location of pollen stations



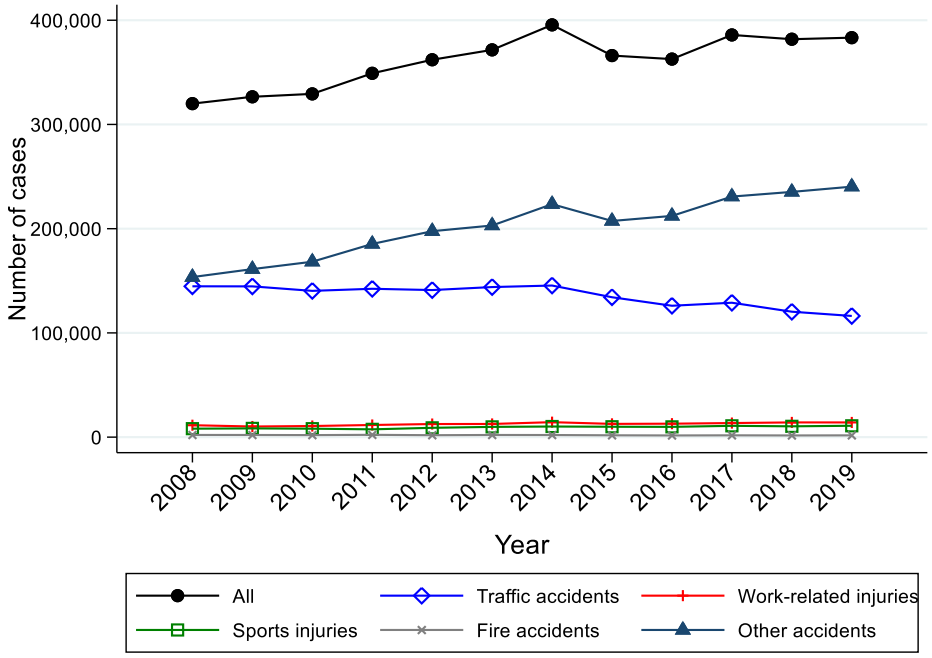
Notes: There is a total of 120 pollen stations in Japan. There are 47 prefectures in Japan, and each prefecture has, on average, 2–3 stations except for Okinawa. Okinawa, which is located the furthest south and has a different climate from the rest of the country, has no stations as pollen is not observed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

Figure A5—Distance to the pollen monitoring stations



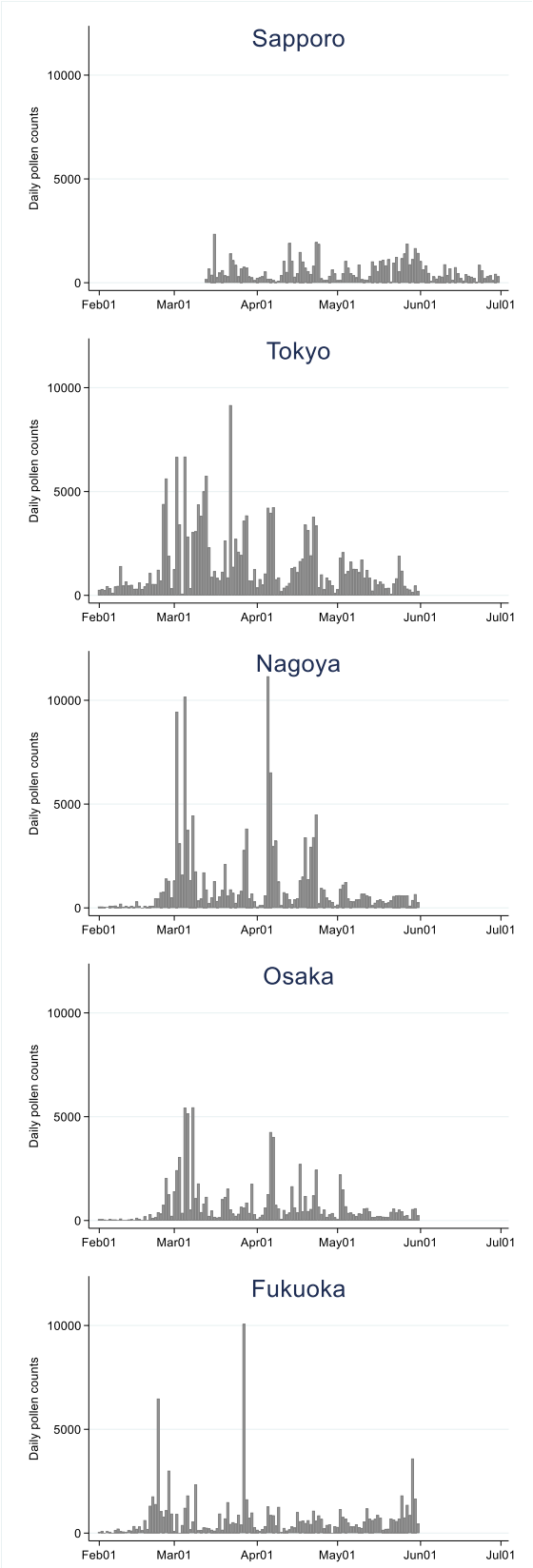
Notes: The figure plots the cumulative distribution of distance from the centroid of units (N=705) to the nearest pollen monitoring stations (N= 120). The vertical dotted line corresponds to 48 km (30 miles) which is used by Chalfin et al. (2019). 90.2% (636 out of 705) are within this threshold.

Figure A6—Time series of accidents cases



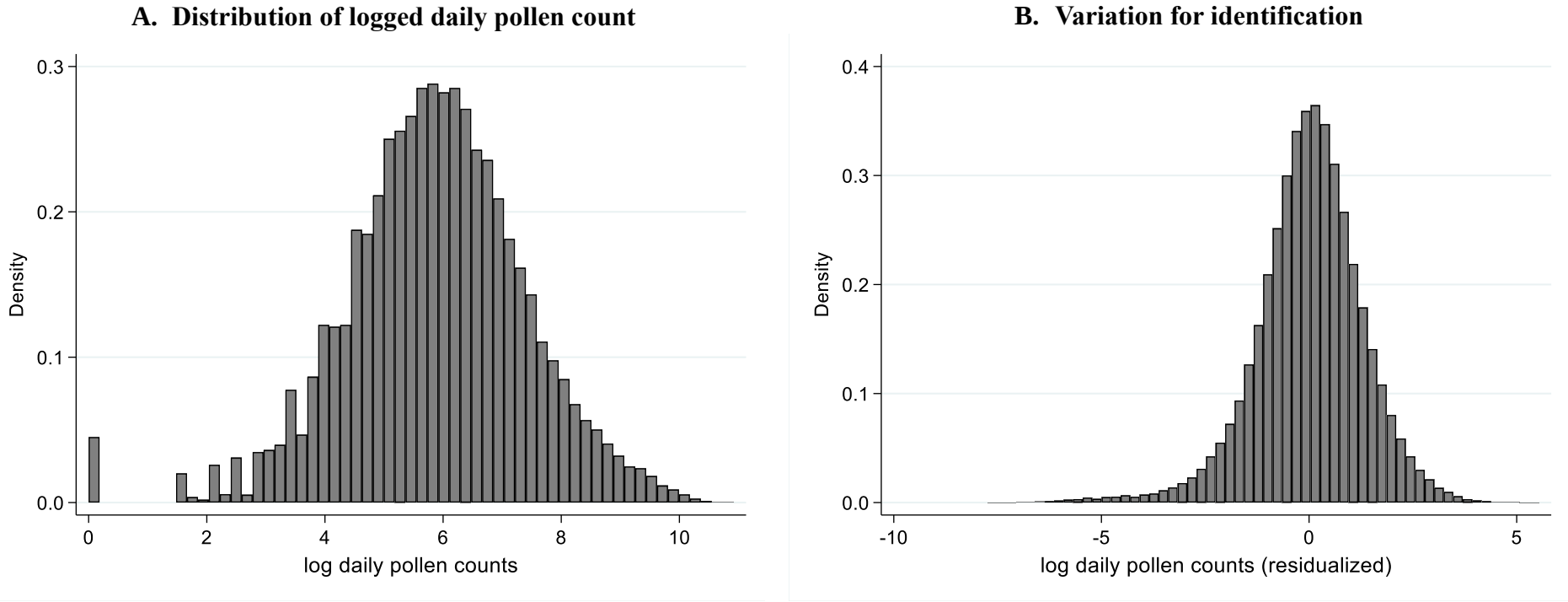
Notes: The graph plots the yearly total cases of all accidents as well as each type from 2008 to 2019.

Figure A7—Daily pollen counts for selected locations



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

Figure A8—Variation in pollen counts



Notes: Panel A displays the histogram of the logged daily pollen count (grains/m^3) from 2008–2019. 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	Years 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 list the brand name of allergy medications with the years of release as well as any particular mention of driving. The ones highlighted in gray are the medications that do not include any specific mention about driving after taking the medications. Note that our primary data on accidents spans from 2008 to 2019.

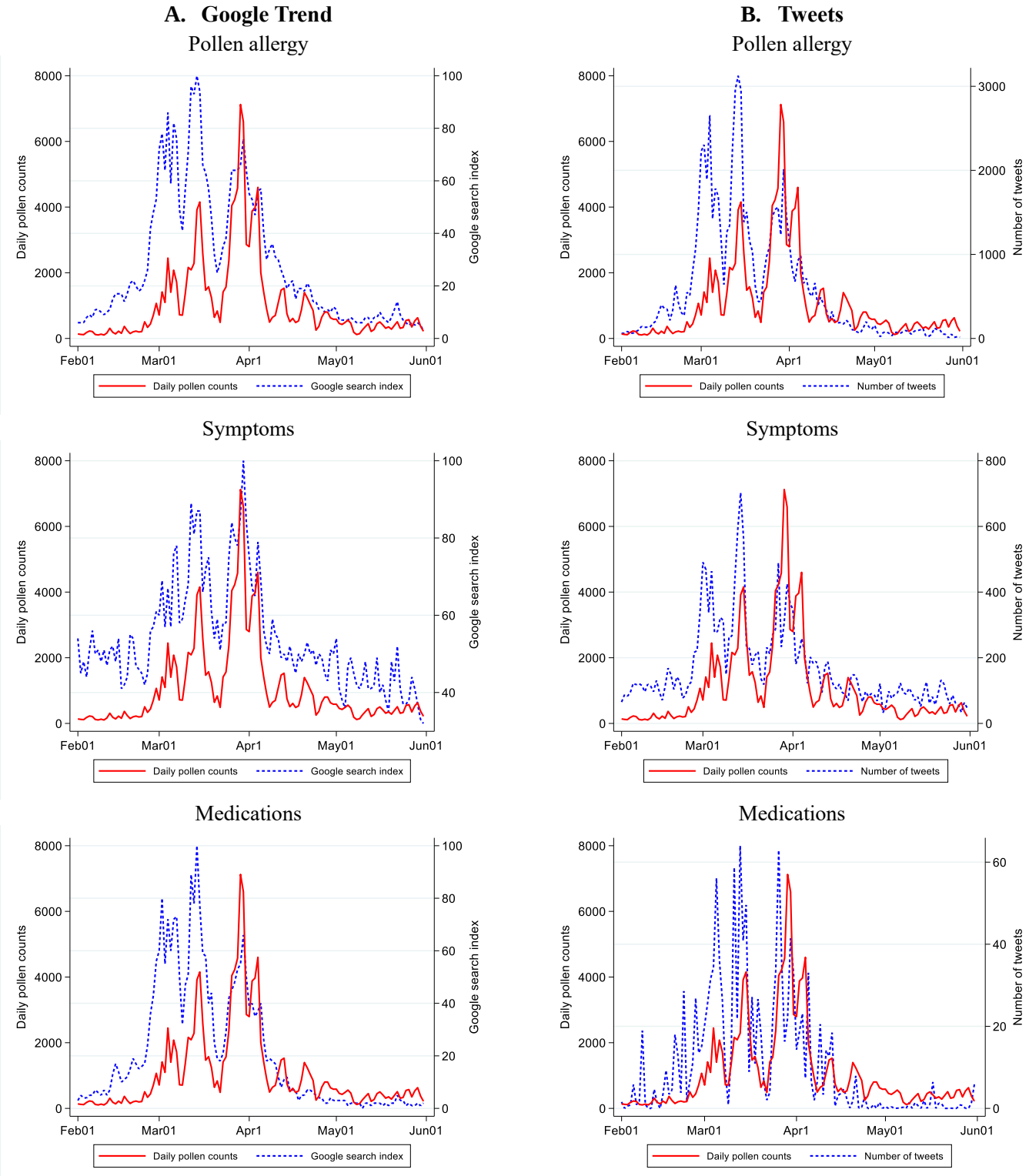
Table A2— Avoidance behaviors with full covariates

	A. All	B. By week		C. By age			
				Non-elderly		Elderly	
		Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log (pollen)	-0.0005	0.0000	-0.0021***	-0.0007	-0.0029***	0.0005	-0.0013
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0006)	(0.0009)
Rain (base: no rain)							
<1 mm	-0.0061***	-0.0059***	-0.0047**	-0.0050***	-0.0032	-0.0121***	-0.0111***
	(0.0013)	(0.0011)	(0.0019)	(0.0011)	(0.0020)	(0.0016)	(0.0027)
1 mm≤ & <2 mm	-0.0167***	-0.0144***	-0.0208***	-0.0089***	-0.0170**	-0.0283***	-0.0365***
	(0.0035)	(0.0024)	(0.0080)	(0.0020)	(0.0077)	(0.0040)	(0.0122)
≥2 mm	-0.0167***	-0.0150***	-0.0249***	-0.0095**	-0.0162*	-0.0334***	-0.0466***
	(0.0045)	(0.0041)	(0.0082)	(0.0042)	(0.0086)	(0.0057)	(0.0095)
Mean temperature (base: <0 ℃)							
[0, 5) ℃	0.0018	0.0068**	0.0096	0.0029	0.0139	0.0048	0.0114
	(0.0033)	(0.0034)	(0.0064)	(0.0043)	(0.0091)	(0.0040)	(0.0102)
[5,10) ℃	0.0111***	0.0139***	0.0189***	0.0081*	0.0214**	0.0154***	0.0270**
	(0.0036)	(0.0037)	(0.0067)	(0.0045)	(0.0101)	(0.0044)	(0.0109)
[10,15) ℃	0.0089**	0.0120***	0.0160**	0.0095*	0.0189*	0.0102**	0.0214*
	(0.0043)	(0.0043)	(0.0070)	(0.0049)	(0.0101)	(0.0050)	(0.0108)
[15,20) ℃	0.0061	0.0094*	0.0172**	0.0064	0.0201*	0.0074	0.0211**
	(0.0045)	(0.0049)	(0.0068)	(0.0054)	(0.0103)	(0.0053)	(0.0106)
[20,25) ℃	0.0120***	0.0165***	0.0200***	0.0121**	0.0218**	0.0134**	0.0235**
	(0.0043)	(0.0046)	(0.0069)	(0.0056)	(0.0096)	(0.0055)	(0.0101)
≥ 25 ℃	0.0273***	0.0264***	0.0319***	0.0291***	0.0577***	0.0317***	0.0284
	(0.0057)	(0.0066)	(0.0079)	(0.0084)	(0.0212)	(0.0090)	(0.0180)
Mean wind speed	-0.0022***	-0.0021***	-0.0023***	-0.0019***	-0.0028***	-0.0026***	-0.0023**
	(0.0005)	(0.0005)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0009)
Darkness	-0.0084***	-0.0090***	-0.0073***	-0.0112***	-0.0047*	-0.0140***	-0.0068**
	(0.0014)	(0.0012)	(0.0023)	(0.0014)	(0.0028)	(0.0011)	(0.0027)
log (population)	1.3108***	1.2630***	1.4497***	1.4971***	1.7499***	0.8839***	0.9482***
	(0.1975)	(0.1997)	(0.2074)	(0.2136)	(0.2289)	(0.2159)	(0.2205)
R-squared	0.98	0.99	0.99	0.97	0.97	0.97	0.97
N	478,853	343,454	135,399	475,883	474,635	474,635	474,635
Pref FE	X	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X	X
Month-year FE	X	X	X	X	X	X	X
Month-prefecture FE	X	X	X	X	X	X	X

Notes: The sample comes from 2014–2019 (Feb-May) cell-phone location data, 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 outcome is the logged daily number of people staying outside at 2 pm. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

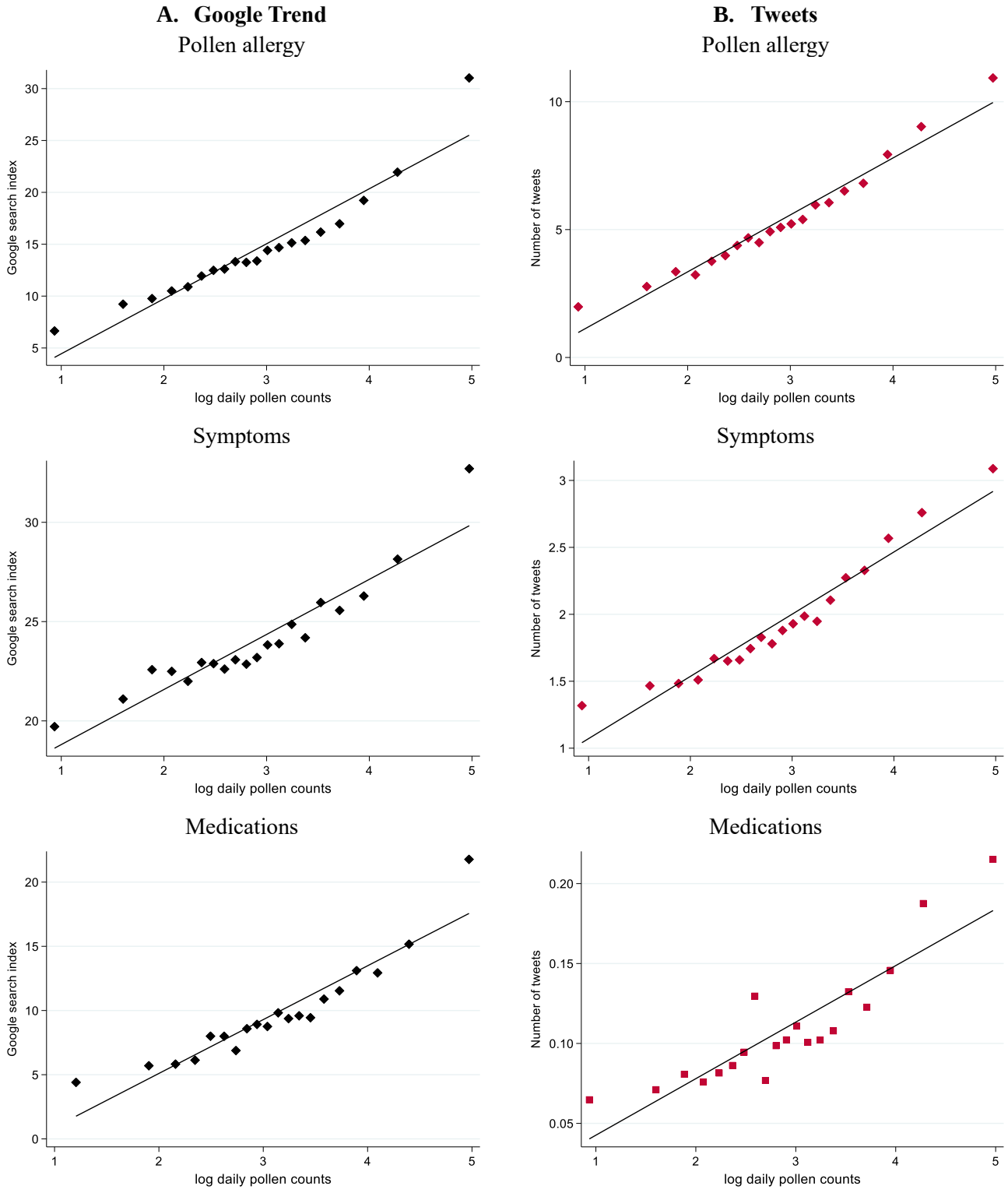
Appendix B: Google Trend and Tweets

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



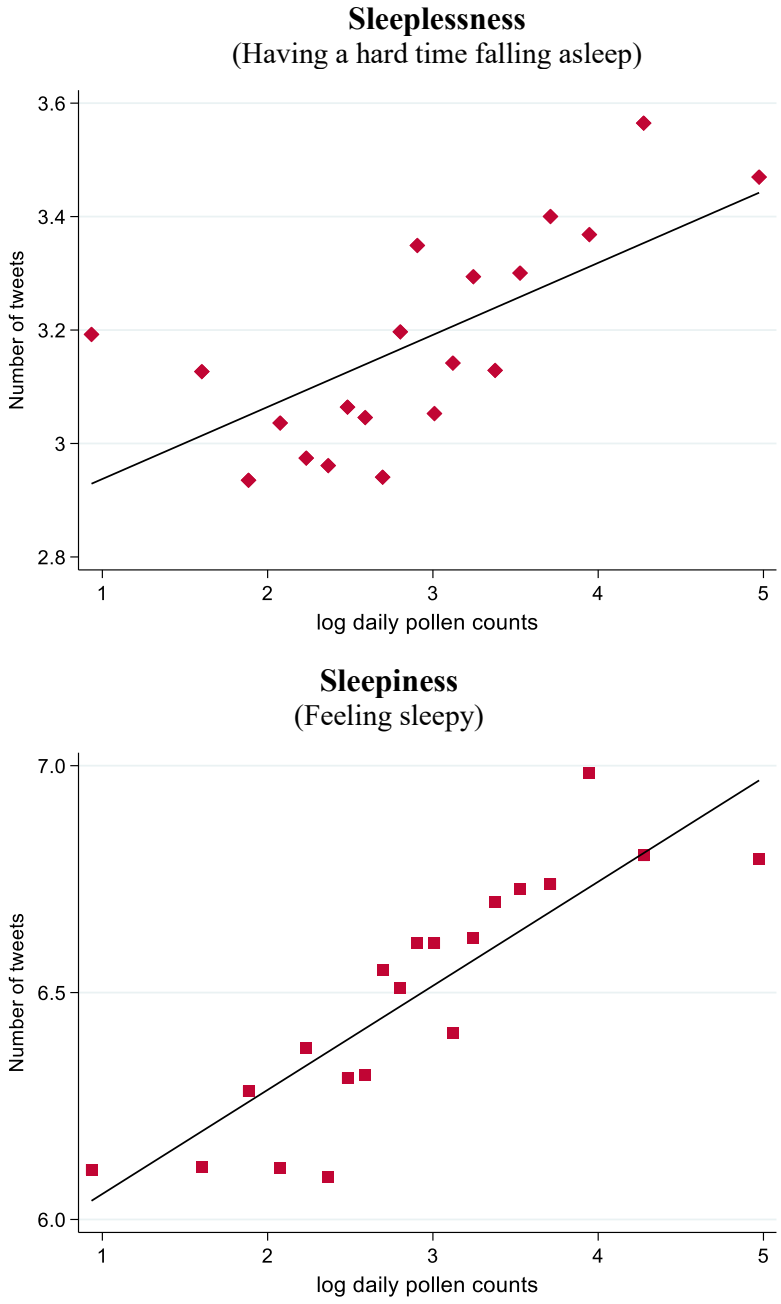
Notes: The figure shows the time series patterns of the average daily pollen counts (grains/m^3) and Google search index in Panel A and the number of Tweets for Panel B for pollen allergy-related, symptom-related, and medication-related keywords in 2018 at the country level. See Table B1 for the list 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 comes from 2016–2019 Google Trend data for Panel A and 2016–2019 Twitter data 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, symptoms-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 comes from 2016–2019 Twitter data, 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 comes from 2016–2019 Google Trend data for Panel A and 2016–2019 Twitter data 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

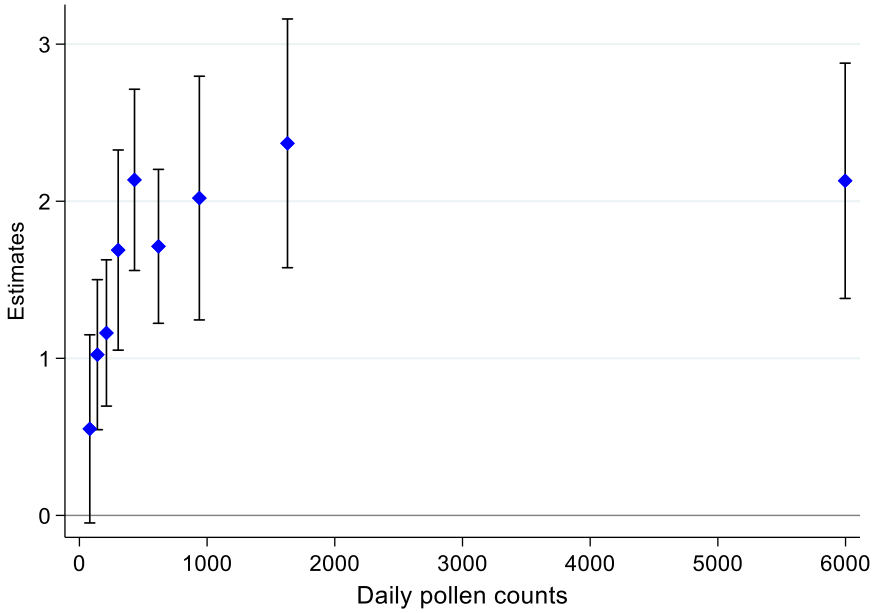
	(1)	(2)	(3)
Sleeplessness			
log (pollen)	0.138**	0.148**	0.130
	(0.057)	(0.062)	(0.078)
R-squared	0.72	0.72	0.73
N	21,551	21,551	21,433
Mean of dep. var	3.18	3.18	3.15
Sleepiness			
log (pollen)	0.171*	0.210**	0.174
	(0.089)	(0.093)	(0.118)
R-squared	0.84	0.84	0.84
N	21,551	21,551	21,433
Mean of dep. 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 comes from 2016–2019 Twitter data, 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

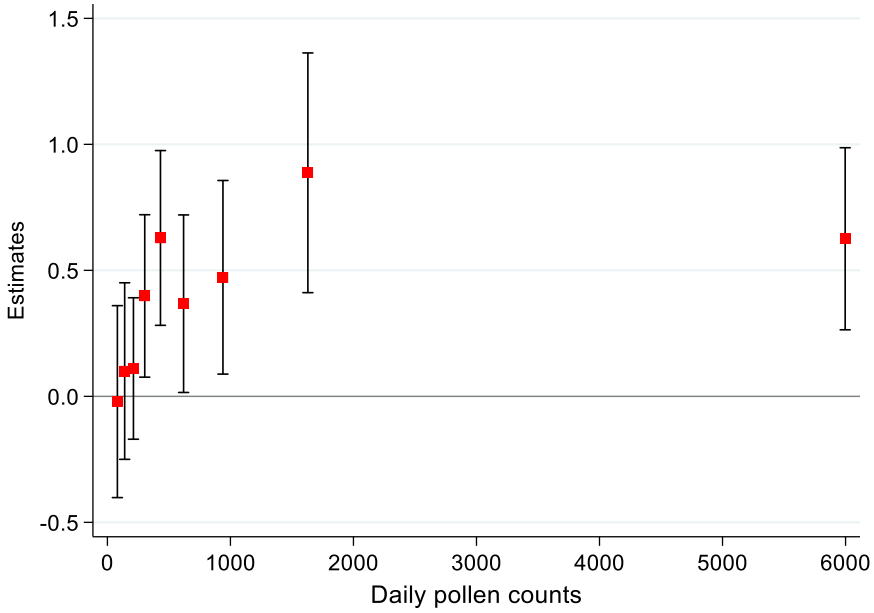
Appendix C: Ambulance records

Figure C1—Dose responses

A. All accidents

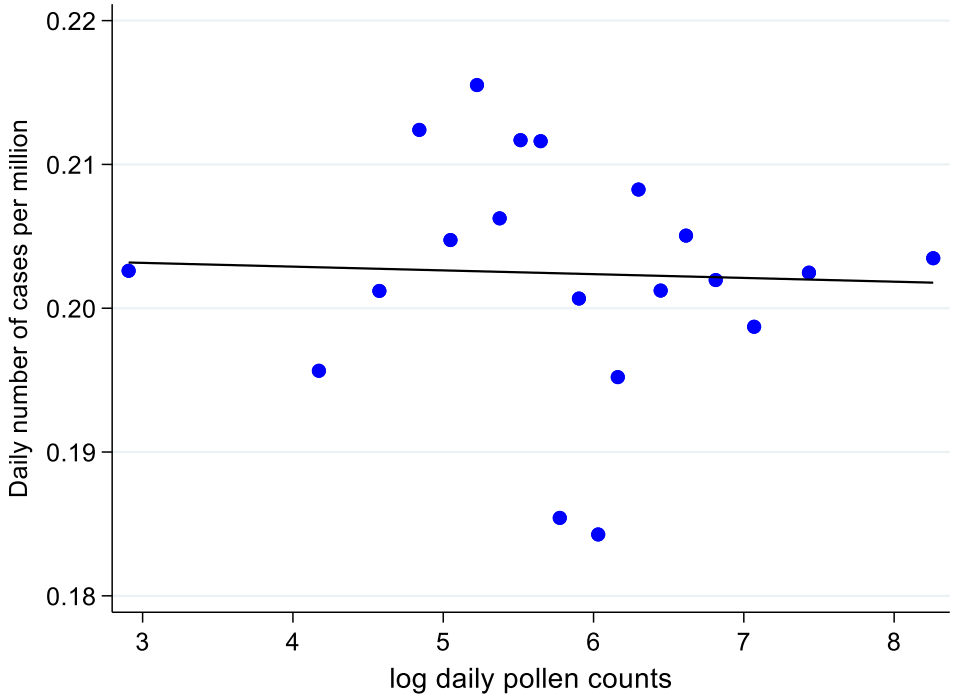


B. Traffic accidents



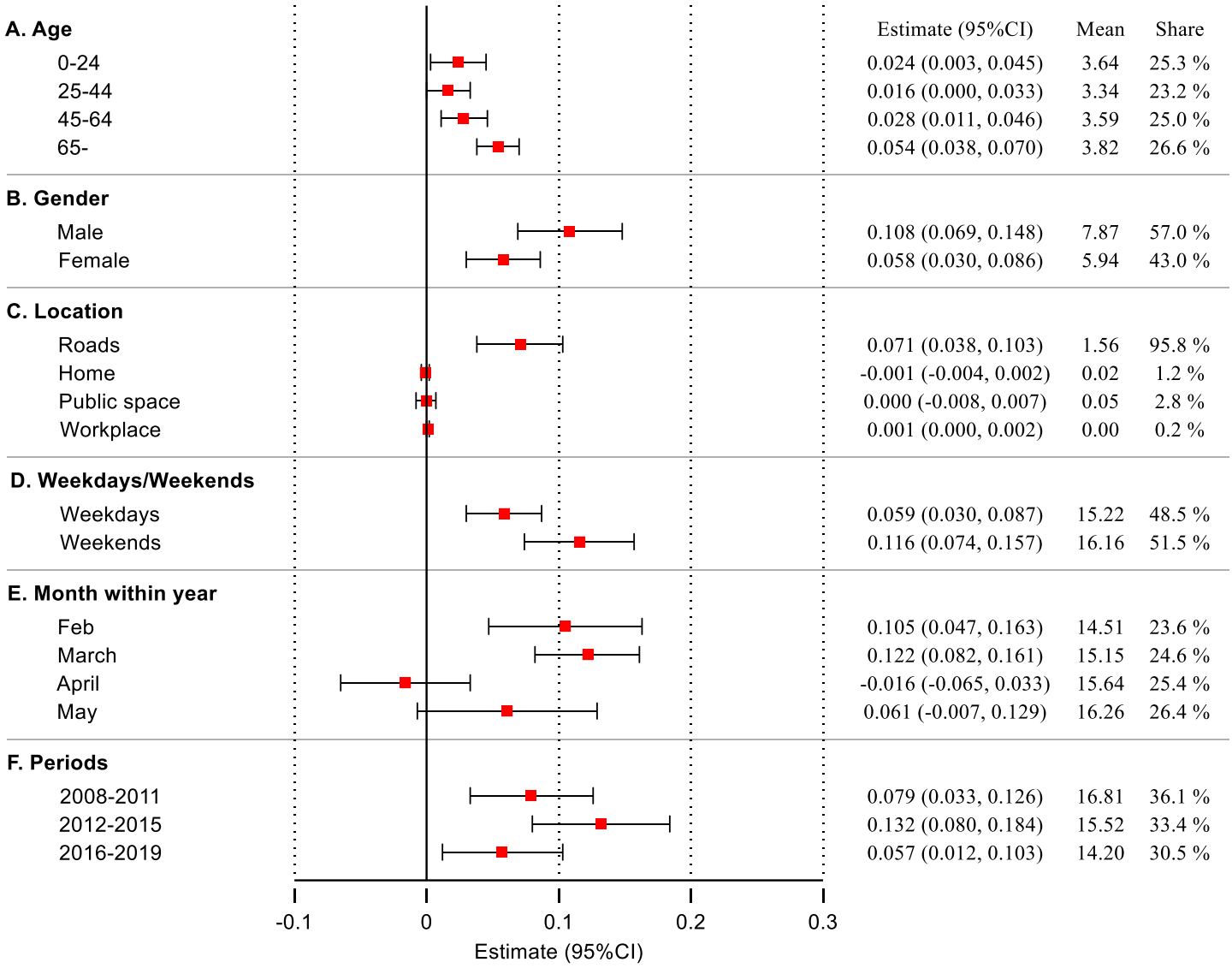
Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95 percent confidence interval of treatment effects of daily pollen count (in levels) from the variant of equation [1], where the daily pollen counts are divided into deciles. 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 is 35.8%. 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 comes from 2015–2019 ambulance records, 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.

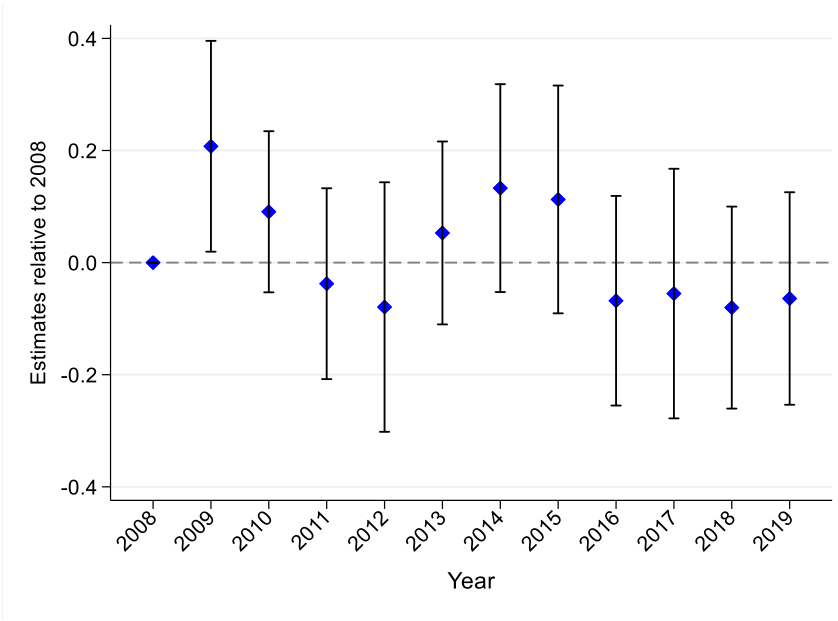
Figure C3—Other heterogeneous treatment effects (Traffic accidents)



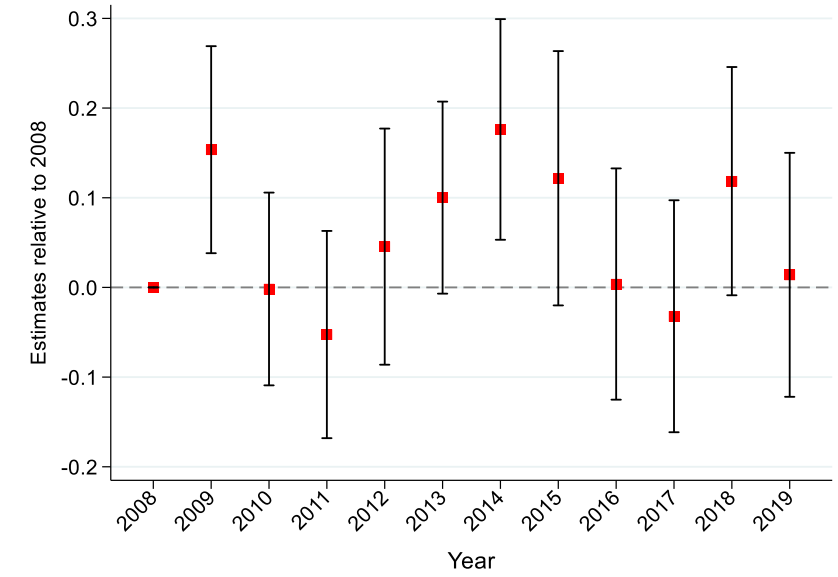
Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The graphs display the estimates and 95 percent confidence interval of heterogeneous treatment effects of logged daily pollen count from equation [1]. The 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 35.8%. 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 reported second to the far right is the number of daily cases per million people. The share reported on the far right is summed to 100 percent within the panels.

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

A. All accidents



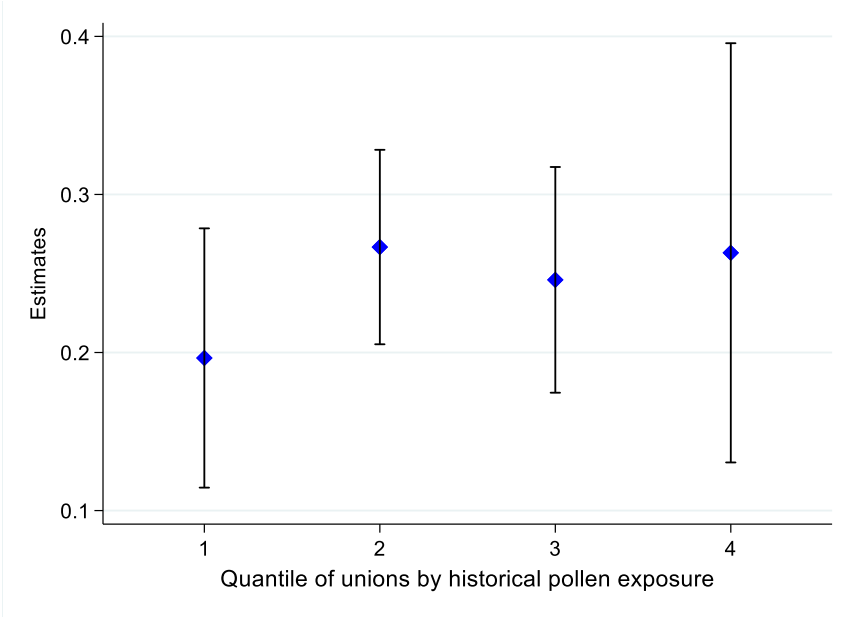
B. Traffic accidents



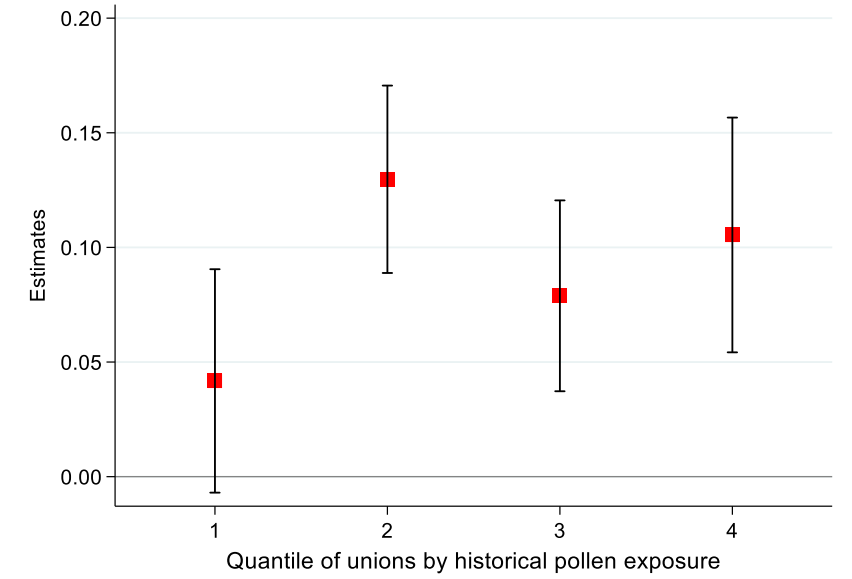
Notes: The sample comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. We add a series of interaction tearms of logged daily pollen count with each year dummy from 2009 to 2019 (2008 as baseline). The graph displays the estimates of a series of interaction tearms, which capture the treatment effects of logged daily pollen count *relative to* the treatment effects in 2008, along with 95 percent 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 is 35.8%. 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

C. All accidents



D. Traffic accidents



Notes: The sample comes from 2008–2019 ambulance records, 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 percent 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 mean of pollen counts during 2008–2019 for each unit and divide the units into quantiles. The lower quantile indicates that the units suffer relatively lower pollen exposure on average, while the higher quantile indicates higher pollen exposure. The share of traffic accidents (Panel B) among all accidents is 35.8%. 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) of 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)	0.228***	0.214***	0.232***	0.238***	0.276***	0.328***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.023)	(0.024)
R-squared	0.47	0.47	0.47	0.47	0.47	0.50
N	970,309	970,309	970,309	970,309	970,309	969,623
Mean of dep. var	43.21	43.21	43.21	43.21	43.21	43.21
B. Traffic accidents						
log (pollen)	0.079***	0.079***	0.090***	0.084***	0.117***	0.139***
	(0.012)	(0.012)	(0.013)	(0.012)	(0.014)	(0.015)
R-squared	0.25	0.25	0.24	0.25	0.25	0.25
N	970,309	970,309	970,309	970,309	970,309	970,306
Mean of dep. var	15.48	15.48	15.48	15.48	15.48	15.48
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 comes from 2008–2019 ambulance records, 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 is 35.8%. 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	
		0.228		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	(0.017)	***	(0.012)	***
Prefecture and date	47 + 1796	(0.025)	***	(0.016)	***
Prefecture and month-year	47 + 60	(0.028)	***	(0.018)	***

Notes: The sample comes from 2008–2019 ambulance records, 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 is 35.8%. 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)	0.228***	0.0054***	0.030***
	(0.017)	(0.0006)	(0.003)
R-squared	0.47	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	0.25	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 comes from 2008–2019 ambulance records, and the level of observation is a unit per day (N= 970,309). There are 705 units in total. The share of traffic accidents among all accidents is 35.8%. 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. The standard errors clustered at pollen monitoring station levels are reported in parentheses. 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) along with the standard errors clustered at pollen monitoring station levels 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)	0.228***	-0.000	0.020
	(0.017)	(0.020)	(0.021)
R-squared	0.47	0.47	0.47
N	970,309	879,342	879,326
Mean of dep. var	43.21	43.51	42.93
B. Traffic accidents			
log (pollen)	0.079***	-0.020	-0.001
	(0.012)	(0.012)	(0.011)
R-squared	0.25	0.25	0.25
N	970,309	879,342	879,326
Mean of dep. var	15.48	15.32	15.68
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 comes from 2008–2019 ambulance records, 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 an 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 in 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 is 35.8%. Estimates are weighted by the population in each unit. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table C5—Controlling avoidance behaviors (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 people outside)		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 comes from 2014–2019 ambulance records 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 a variant of 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) just add the logged number of people staying outside at 2 pm 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

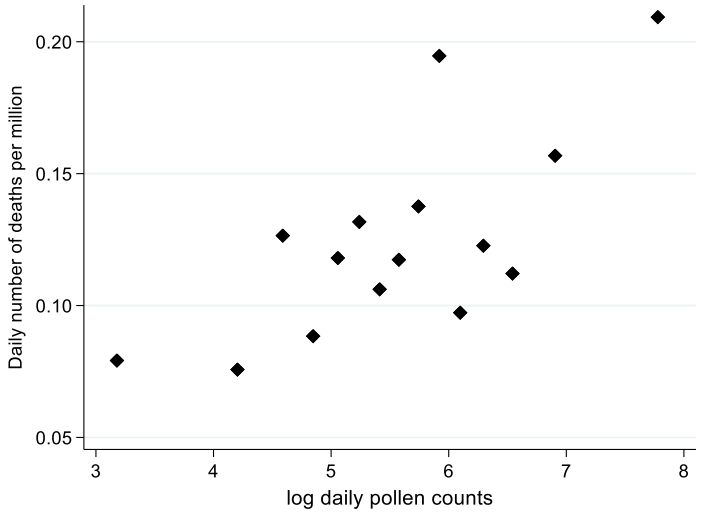
Appendix D: Police records

Police records contain all 690,415 (or 106,533 in pollen season) traffic accidents in 2019 and 2020. The data is at the individual level and includes information on the location and the exact date and time of the accident. 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 summing across 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 a 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/fetal estimates for traffic accidents during 2008–2019 ambulance records (column (1) of Panel B from Table 4). Column (2) reports the mortality estimates during 2019–2020 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 slightly underestimate the effect of pollen exposure on the deaths from traffic accidents. However, the two estimates are not statistically distinguishable at the convtional level.

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



Notes: The sample comes from 2019–2020 police records, and the level of observation is municipality per day (N = 399,749). There are 1,700 municipalities in total. The graphs display 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 from the traffic accidents after controlling for the municipality, month-by-year, month-by-prefecture, and day-of-week FEs.

Table D1— Mortality from 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) comes from 2008-2019 ambulance records, while the sample for column (2) comes from 2019–2020 police records. The level of observation is unit per day for column (1) and municipality per day for column (2). There are 705 units and 1700 municipalities in total. The dependent variable is the number of deaths from 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 Column (1) of Panel B in Table 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: Data Appendix

Data	Source
Ambulance records	Years: 2008–2019 (detailed diagnosis information is available from 2015 on) Data description: Universe of ambulance records 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: Universe of traffic accidents records that involves injuries or deaths Source: National Policy Agency (NPA) https://www.npa.go.jp/publications/statistics/koutsuu/opendata/index_opendata.html
Pollen	Years: 2008–2019 Data description: Hourly pollen counts from 120 stations as well as hourly rainfall, temperature, wind speed, and wind direction from nearby weather stations during the pollen 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
Cell-phone data	Years: 2014–2019 Data description: called 'Mobile Spatial Statistics' data which are the population estimates based on the location information of 78 million cell-phone users of NTT Docomo Source: NTT Docomo, Inc https://mobaku.jp/ (in Japanese)