The Impact of Air Pollution on Petcare Utilization*

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Abstract

Air pollution is one of the leading causes of morbidity and premature mortality globally. A large literature documents the adverse impacts of ambient air pollution on human health. In contrast, there is a lack of comparable research studying the effects of air pollution on animal health. We fill this gap, utilizing five years of data on over seven million visits to veterinary practices across the United Kingdom. Leveraging within-city variation in daily monitor-measured air pollution levels, we find that increases in fine particulate matter (i.e., $PM_{2.5}$) are associated with significant increases in the number of vet visits for both cats and dogs. In aggregate, these estimates suggest that reducing ambient $PM_{2.5}$ levels to a maximum of 5 micrograms per cubic meter as recommended by the World Health Organization would result in a 0.7-2.5% reduction in vet visits.

JEL Codes: I0, Q51, Q53, Q57

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1 Introduction

One in every six human deaths in 2019 was attributed to air pollution Fuller et al. (2022). The primary driver of air pollution-related mortality is exposure to fine particulate matter Dominici, Greenstone and Sunstein (2014); Muller, Mendelsohn and Nordhaus (2011); Pozzer et al. (2023); Institute for Health Metrics and Evaluation (2024). A large body of empirical evidence documents the link between increased exposure to fine particulate matter and a host of human health outcomes, including respiratory, cardiovascular, and neurological conditions that can lead to increased emergency department visits, hospitalizations, and premature mortality Dockery et al. (1993); Krewski et al. (2009); Beelen et al. (2014); Ebenstein et al. (2017); Ebenstein, Lavy and Roth (2016); Deryugina et al. (2019); Shi et al. (2023). In contrast, empirical research on the effects of air pollution on animal health remains limited, with no studies to date investigating impacts on pet health using large-scale population data. The limited existing evidence is primarily correlational, relying on associations observed in small-scale observational or clinical studies Lin et al. (2018); Lin, Lo and Wu (2020). This is despite humans and pets sharing many of the same biological pathways and exposure levels that lead to morbidity and mortality Losacco and Perillo (2017).

Pet owners place particular value on the well-being of their pets. In 2022, households spent about $120 billion on pets in the United States and £10 billion in the United Kingdom, with spending patterns in pet healthcare closely reflecting those in human healthcare Bloomberg Intelligence (2023); Office for National Statistics (2024); Einav, Finkelstein and Gupta (2017). The well-documented negative effects of air pollution on human health, coupled with the large pet population and the substantial economic resources devoted to their care, underscore the need for a rigorous evaluation of air pollution's impact on pet health.

We use visit-level data from an extensive sample of veterinary practices across the United Kingdom to estimate the impact of fine particulate exposure (i.e., $PM_{2.5}$) on the utilization of pet healthcare. The sample includes seven million vet visits for cats and dogs over five years, which we combine with data on ambient air quality from nearby pollution monitors. Estimates from panel data regressions that leverage daily variation in air pollution and control for a wide range of confounding factors indicate that a one microgram per cubic meter increase in average $PM_{2.5}$ over the preceding week corresponds to a 0.7% increase in vet visits for both cats and dogs. This implies that moving from a low pollution period, with $PM_{2.5}$ below 5µg/m^3, to a high pollution period, with $PM_{2.5}$ of 40-50µg/m^3, translates into a 30-40% increase in expected total vet visits. The effects we find for pets are of a similar order of magnitude to studies that have looked at human health and hospitalizations Atkinson et al. (2014); Requia et al. (2018); Deryugina et al. (2019).

We further substantiate these findings by demonstrating that the estimates remain similar when using an instrumental variables (IV) approach that helps mitigate concerns about possible measurement error in our measure of air pollution. In this IV framework, we focus on variation in $PM_{2.5}$ concentration levels driven by thermal inversions and changes in wind direction. Thermal inversions occur when atmospheric temperatures increase with altitude, inhibiting the vertical dispersion of air pollutants and trapping them near the surface. Changes in wind direction influence local air quality by either dispersing locally generated pollutants or transporting pollutants from distant sources. These weather phenomena are unlikely to be related to veterinary visits except through their effects on air quality Deryugina et al. (2019); Sager (2019); Chen, Oliva and Zhang (2022).

In aggregate, our findings suggest that reducing ambient $PM_{2.5}$ levels to a maximum of 5 $\mu g/m^3$ as recommended by the World Health Organization (WHO) would result in a reduction in vet visits of 0.7% to 2.5% (approximately 80,000 to 290,000 fewer vet visits each year in the UK) Organization (2021). This entails an annual savings in petcare utilization costs, owner time, and travel costs of roughly 19 to 66 million pounds. Importantly, this is only some of the many benefits of reducing air pollution enjoyed by pets and their owners. For example, our annual savings do not encompass reductions in pet mortality and morbidity, owners' emotional distress caused by pet sickness, or increased time spent enjoying companionship due to improved pet lifetimes. The full economic benefits of improved air quality are likely substantially larger than those captured in our calculation, highlighting the need for further work to quantify and monetize the full benefits to pets and their owners Sunstein (2024); Budolfson et al. (2024).

While the relationship between air pollution and animal health has long been recognized—and has informed epidemiological insights into the health effects of pollution on humans Catcott (1961); Reif (2011)—most existing research has focused on documenting statistical associations rather than establishing causal links. Prior studies typically rely on small-scale observational data or clinical laboratory experiments Ni et al. (2021); Ivester, Couëtil and Zimmerman (2014); Sanderfoot and Holloway (2017); Calderón-Garcidueñas et al. (2017), including a limited number of small-sample studies examining pet cats and dogs Lin et al. (2018); Lin, Lo and Wu (2020). Only a few studies to date have leveraged quasi-experimental variation in air pollution exposure to estimate its effects on wildlife and farm animals—such as on bird abundance Liang et al. (2020) or dairy cow mortality Cox et al. (2016). However, to our knowledge, no study utilizing quasi-experimental variation in air pollution exposure has focused on the large and economically significant pet companion population.

Here we bring the same rigorous empirical methods that have been used in recent human health studies to provide new evidence of the effect of air pollution on pet dogs and cats. Closest to this work in scale is research using the Italian National Canine Registry to examine the relationship between heavy metals pollution and the life expectancy of dogs Giugliano et al. (2024). We contribute to this small literature by providing the first large-scale empirical analysis of the health impacts of air pollution on pets using econometric methods and data on 3.8 million unique cats and dogs. The estimated effects yield new insights into how environmental stressors influence the provision of pet healthcare and offer empirical evidence that can be used to quantify the value of pet health improvements in regulatory impact analyses of air quality. The omission of animal welfare in such evaluations has been termed an 'inexcusable gap', highlighting the importance of further research in this area Sunstein (2024).

2 Results

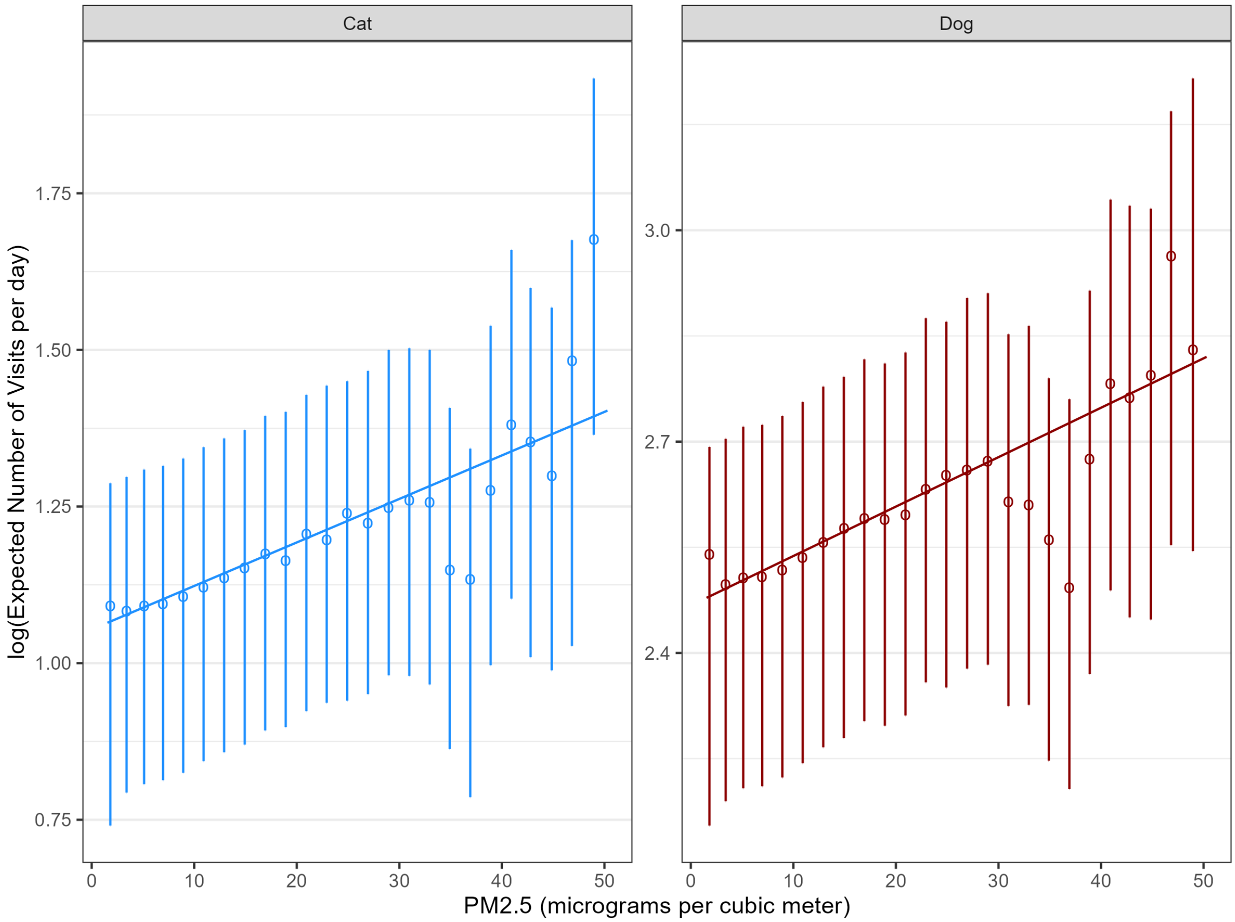
2.1 All-Cause Vet Visits

Figure 1 presents estimates of the effect of $PM_{2.5}$ on the number of veterinary visits across all causes. In all cases, the estimates reflect the effect of an increase in weekly average $PM_{2.5}$ for the preceding seven day period, including the date of the visit. We estimate the effect of $PM_{2.5}$ on vet visits separately for cats and dogs. Considering only air pollution on the seven preceding days reflects that scheduling veterinary visits in the UK is generally straightforward, with many appointments available on the same day or the following day.

Since the dependent variable is the count of vet visits, we estimate the relationship using a binscatter Poisson regression model Cattaneo et al. (2024). This approach flexibly estimates the relationship between the number of vet visits and $PM_{2.5}$, while controlling for differences in pet age, sex, and weather. We also include NUTS3 region and day-of-sample fixed effects to control for all observed and unobserved factors that predict vet visits and vary across NUTS3 regions (e.g., persistent differences in socioeconomic status across region) or across days (e.g., seasonality of vet visits and overall economic trends). Each circle marker corresponds to a point estimate and the whiskers display the 95% confidence intervals for each estimate. We provide further details on the data sources and methodology in the SI Appendix.

For both species, the effect of $PM_{2.5}$ on log expected number of visits is linearly increasing and statistically significant, with a clear trend of more visits on more polluted days. For example, moving from a low pollution period, with $PM_{2.5}$ below 5µg/m^3, to a high pollution period, with $PM_{2.5}$ of 40-50µg/m^3, translates into a 30-40% increase in expected total vet visits. Estimates at the upper end of the $PM_{2.5}$ distribution are noisier (though still statistically significant), and more divergent from the fitted line.

Figure 1: Estimated Relationship Between Number of Vet Visits and Ambient $PM_{2.5}$



Notes: This figure presents Poisson regression estimates and 95% confidence intervals of the impact of $PM_{2.5}$ concentration levels on the count of vet visits. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. We utilize the binscatter method to show how visits change as pollution increases. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

Table 1 reports point estimates from a Poisson regression model that controls for the same covariates and fixed effects as in Figure 1 but fits a linear relationship between log expected vet visits and $PM_{2.5}$ (as suggested by Figure 1). In the main specification (columns 1 and

2), we find that a one microgram per cubic meter increase in $PM_{2.5}$ corresponds to a 0.7% increase in daily expected number of visits for both cats and dogs ($p < 0.05$).[1]

Table 1: Estimated Effect of Ambient $PM_{2.5}$ on Total Number of Vet Visits

Model:	(1)	(2)	(3)	(4)
Variables				
PM2.5	0.0070^{*}	0.0071^{**}	0.0070^{***}	0.0055^{***}
	(0.0038)	(0.0036)	(0.0023)	(0.0021)
Species	Cat	Dog	Cat	Dog
IV	No	No	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.042	13.45	5.042	13.45
Fixed-effects				
NUTS3 Area	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	355,705	355,872	355,705	355,872
Squared Correlation	0.82377	0.84239	0.82377	0.84239
Pseudo R^2	1.3457	1.1118	1.3457	1.1118
BIC	6.2×10^{11}	1.04×10^{12}	6.2×10^{11}	1.04×10^{12}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We also estimate Poisson regression specifications instrumenting for air pollution using wind direction and thermal inversion events (Columns 3-4). We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

We also estimate the impact of $PM_{2.5}$ on vet visits using an instrumental variable estimator that leverages variation in air pollution driven by thermal inversions and wind direction. Here we find a similar effect: a one microgram per cubic meter increase in $PM_{2.5}$ increases expected total visits by 0.6-0.7%. As well as being more precisely estimated, the similar magnitude of the estimated effect provides additional reassurance that our baseline estimates

[1] A one standard deviation increase in $PM_{2.5}$ corresponds to a 3.4% increase in expected vet visits for both cats and dogs.

are attributable to fine particulate matter (as opposed to other factors) and are not biased by measurement error.

These estimated effect sizes are of a similar order of magnitude to those found in human health studies on air pollution and hospitalizations. Systematic reviews have found that a 10 µg/m^3 increase in daily $PM_{2.5}$ leads to a roughly 1% increase in all-cause hospital admissions Atkinson et al. (2014); Requia et al. (2018).[2] A more recent study that uses a similar empirical approach to ours found that a 10 µg/m^3 increase in daily $PM_{2.5}$ leads to a 2.2% increase in one-day all-cause hospitalizations among US Medicare recipients Deryugina et al. (2019). If we convert our estimates into comparable units, they suggest that an equivalent 10 µg/m^3 increase in weekly average $PM_{2.5}$ leads to a roughly 7% increase in expected all-cause veterinary visits. When estimating our regressions using contemporaneous daily average $PM_{2.5}$ instead of the weekly rolling average, we find an effect size of 2% (see SI Appendix C).

2.2 Vet Visits by Main Presenting Complaint

Figure 2 examines how ambient $PM_{2.5}$ affects the number of visits depending on the main presenting complaint. As in Table 1, we report the estimated effects in proportionate terms. Here, we see that the effect of $PM_{2.5}$ on overall vet visits is primarily driven by the "Other Unwell" category: a one microgram per cubic meter increase in $PM_{2.5}$ corresponds to a 1.3% increase in expected daily visits classified as "Other Unwell" for cats, and a 1.2% increase

[2] These effect sizes are consistent with evidence the UK government uses to support its assumptions on the human health impacts of air pollution for use in cost-benefit analysis Atkinson et al. (2014).

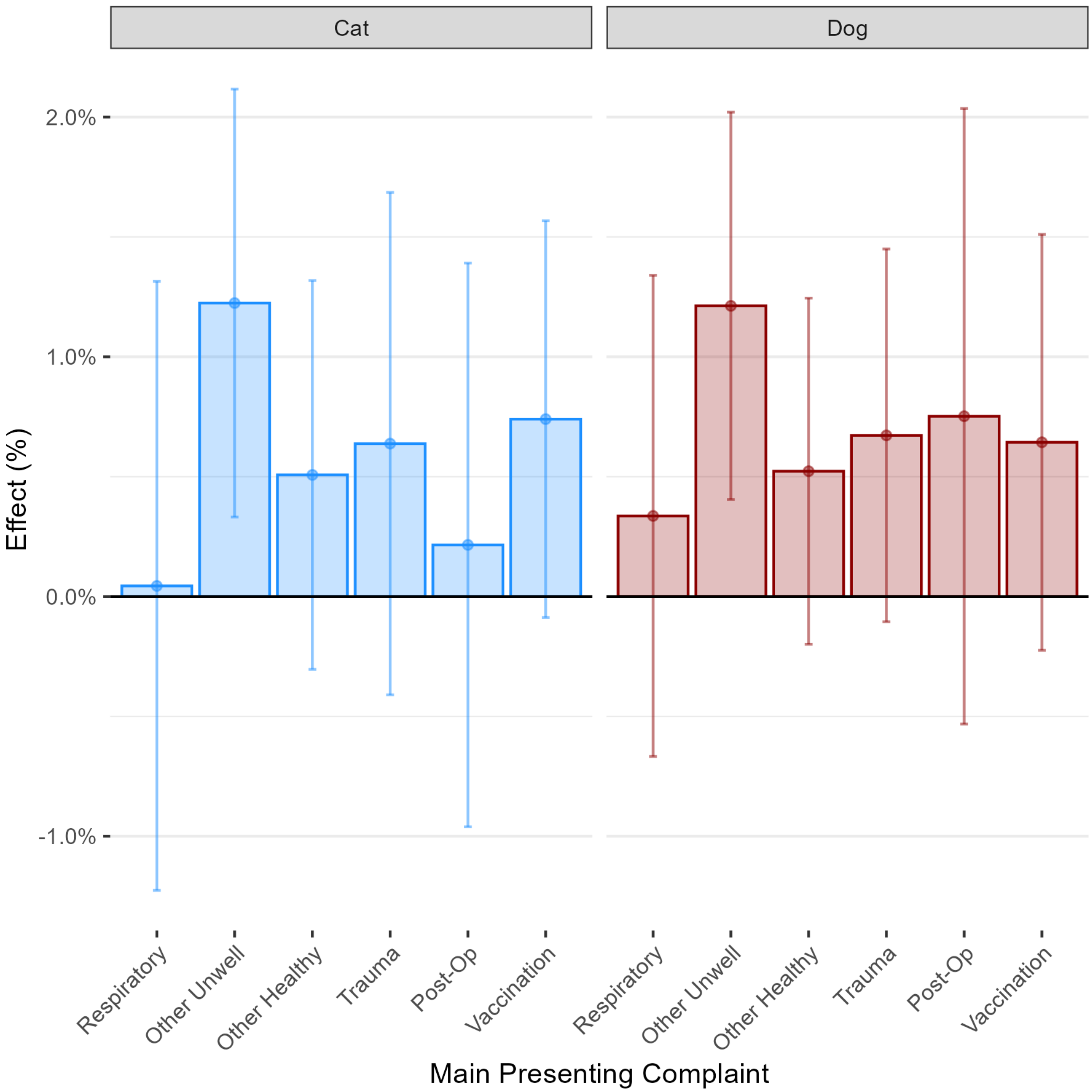
for dogs. Estimates from instrumental variables specifications reveal broadly similar effects and can be found in the SI Appendix C2.

The fact that we can detect a statistically significant effect of $PM_{2.5}$ on "Other Unwell" visits is plausible given that visits for this cause make up roughly a quarter of the total number of visits. Moreover, "Other Unwell" encompasses visits that are not easily categorized into the other more specific options provided, such as vaccinations and trauma. The main impacts of air quality on human health focus on the exacerbation of respiratory, cardiovascular, and neurological conditions. Since there is no main presenting complaint category for cardiovascular or neurological problems, it makes sense that pets with symptoms originating from these sources may be classified in the "Other Unwell" category.

There is a main presenting complaint category for "Respiratory" visits, and here we find no significant effect of $PM_{2.5}$. However, only about 1% of the visits are classified as "Respiratory", indicating that respiratory conditions are rarely classified as the main reason a pet is brought in to the vet. We also do not find large statistically significant effects in the categories of main presenting complaint that almost certainly do not have any epidemiological relationship with air pollution exposure. For example, we do not see consistent statistically significant increases in vet visits for "Vaccination" or "Post-Op" on more polluted days.

However, the reporting of main presenting complaint is likely subject to substantial measurement error. Given this is a voluntary additional piece of data to enter after the visit, veterinarians have limited incentive to report main presenting complaint in a consistent and rigorous manner. This may help explain the large proportion of visits that are classified as "Other Unwell" or "Other Healthy".

Figure 2: Estimated Effect of Ambient $PM_{2.5}$ on Number of Vet Visits by Main Presenting Complaint



Notes: This figure presents Poisson regression estimates and 95% confidence intervals of the impact of $PM_{2.5}$ concentration levels on the count of vet visits by main presenting complaint. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. We estimate separate Poisson regressions for each species and for each main presenting complaint. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

2.3 Vet Visits by Pet Age

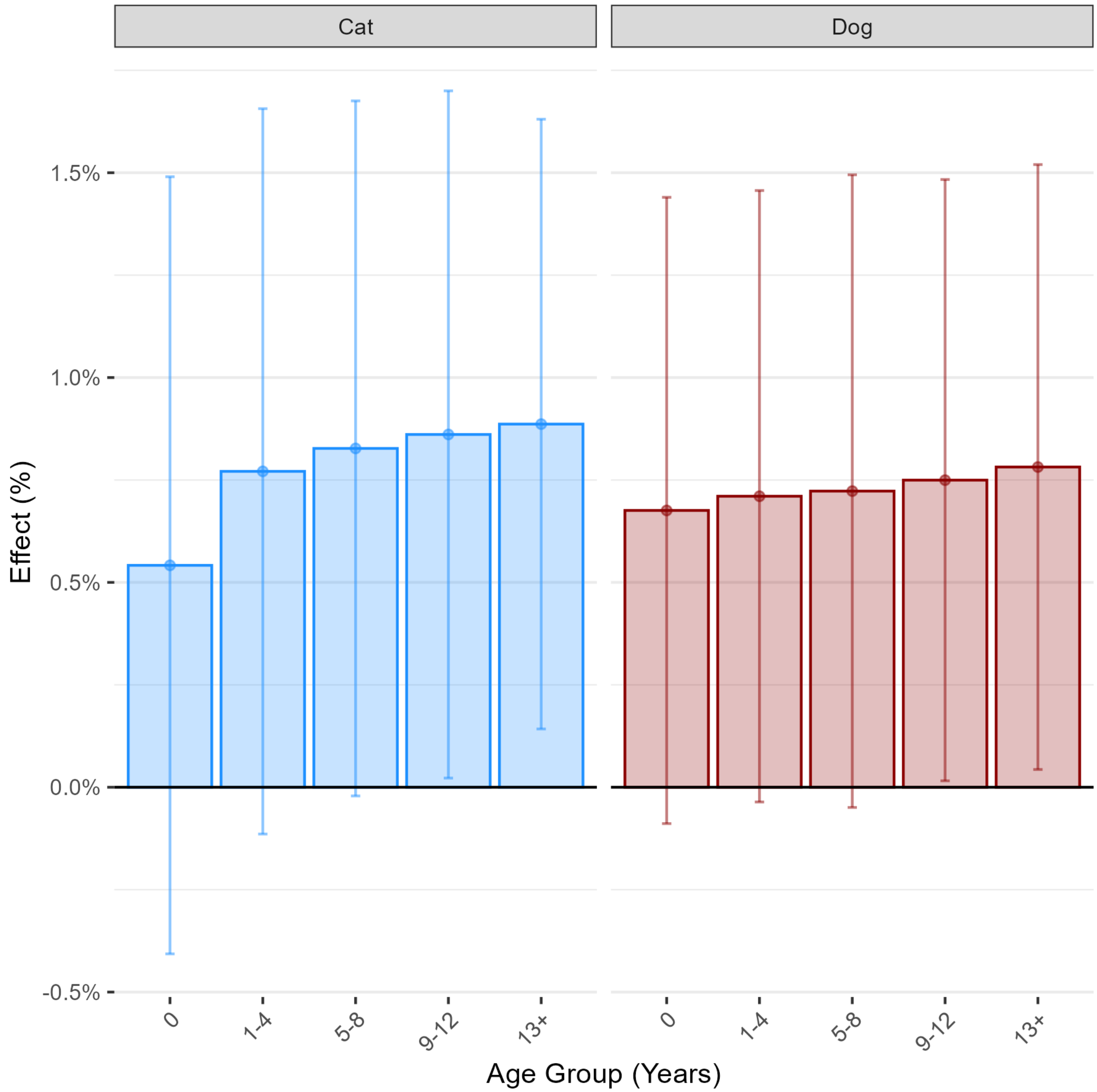
Much of the literature on how air pollution affects human health highlights that vulnerability varies across individuals, with age being a key risk factor Miller et al. (2007); Cesaroni et al. (2013); Deryugina et al. (2019). We therefore explore heterogeneity in our effects by age group. Figure 3 provides age-group-specific estimates of the effect of $PM_{2.5}$ on all-cause visits in proportionate terms. Though we observe an increase in effect size with age, we lack the statistical precision to detect differences across age group bins. Versions of these results using instrumental variables reveal broadly similar effects and can be found in the SI Appendix C2.

We cannot rule out that pet owners may combine multiple purposes into a single visit—such as addressing both acute health concerns triggered by air pollution and routine issues like vaccinations. However, vaccinations—the most likely source of schedulable visits—are heavily concentrated among younger pets, especially in the first year of life. If substitution from low-pollution days to high-pollution days was driving our effects, we might expect larger effects of $\mathrm{PM}_{2.5}$ on vet visits among younger pets for whom vaccinations can be rescheduled. This is not what we observe in Figure 3, suggesting that our estimates do not stem primarily from substitution.

3 Discussion

Using detailed data on more than seven million visits to veterinarian clinics spanning the United Kingdom, we uncover the extent to which ambient fine particulate concentration

Figure 3: Estimated Effect of Ambient $PM_{2.5}$ on Number of All-Cause Vet Visits by Age Group



Notes: This figure presents Poisson regression estimates and 95% confidence intervals of the impact of $PM_{2.5}$ concentration levels on the count of vet visits by age group. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. We estimate separate Poisson regressions for each species and for each age group. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

levels impact petcare utilization. We find that increases in $PM_{2.5}$ concentration levels are associated with significant increases in vet visits for pet cats and dogs. In aggregate, our estimates suggest that reducing ambient $PM_{2.5}$ levels to a maximum of 5 µg/m^3 as recommended by the WHO would result in a reduction in vet visits in the UK of 0.7% to 2.5% (approximately 80,000 to 290,000 fewer vet visits each year in the UK).[3]

Understanding the total economic value of these kinds of improvements in pet health is challenging. Clearly pet owners devote significant time and economic resources to caring for their pets — the pet-care market has grown by over 66% in the last decade, significantly outpacing growth in the wider economy The Economist (2019). If we focus purely on petcare utilization costs, the resulting savings to UK pet owners from moving into compliance with the WHO standard are roughly £18-63 million pounds per year.[4] Adding in the travel and time costs associated with vet visits adds a further £1-3 million pounds per year.[5]

[3]There are approximately 5,000 vet practices in the UK Competition and Markets Authority (2024). The SAVSNET data includes approximately 500 practices. There are 1.2 million all-cause vet visits per year to the 500 practices that participate in the SAVSNET data. If we assume the SAVSNET practices are representative, multiplying by 10 implies 12 million all-cause vet visits per year for the 5000 practices across the entire UK. The population-weighted average level of $PM_{2.5}$ in 2022 was 8.3 µg/m^3. Our all-cause visits treatment effect using weekly average pollution is 0.7% per µg/m^3. To bring UK air pollution concentration levels into compliance with the WHO standard on all days of the year would require reductions in the population-weighted average levels of pollution over the year of 3.6 µg/m^3 in 2022. Multiplying our estimated effect by a change in $PM_{2.5}$ of 3.6 µg/m^3 would imply an associated reduction in vet visits of 2.5%. Multiplying by the total number of visits yields around 290,000 in 2022. If we use a lower all-cause treatment effect of 0.2% based on contemporaneous daily pollution (see SI Appendix C), meeting the WHO standard would imply an associated reduction in vet visits of 0.7%. Multiplying by the total number of visits yields around 80,000 in 2022.

[4]The UK spends roughly £10 billion per year on pets (Office for National Statistics, 2024). This includes £2.5 billion per year on primary vetcare (Competition and Markets Authority, 2024). Assuming that pollution-related vet visits have the same cost as the average visit, a 0.7-2.5% reduction in visits due to reducing $PM_{2.5}$ to the WHO standard entails £18–63 million per year in avoided primary vetcare spending. The savings could be even larger if accounting for additional cost factors such as specialist care and medicines. Including the associated costs of specialist care, diagnostics and medicines increases total vetcare spending to £5.7 billion per year (Competition and Markets Authority, 2024)— meaning a 0.7-2.5% decrease in visits entails an even larger £41–143 million per year in avoided vetcare spending.

[5]Evidence on the catchment areas of vet practices and the distance traveled by actual pet owners indicates a distance traveled of roughly 5 miles (Competition and Markets Authority, 2024). Based on UK government data on average journey times (UK Department for Transport, 2021) and evidence from a recent UK

However, the total economic benefits are likely to be considerably higher. This is because petcare utilization costs are only a small portion of the total willingness-to-pay to improve pet health. Despite an extensive literature on the economic value of health benefits for humans Viscusi and Masterman (2017), it is striking that there is little equivalent research on the value people place on improving the health of their pets Sunstein (2024). There is only one study we are aware of that has examined this directly by estimating a contingent-valuation-based value of statistical dog life Carlson et al. (2020). Related work has also highlighted the significant value people place on protecting wild animals, including specific "charismatic" animal individuals Richardson and Lewis (2022); Costello et al. (2023).

Here we find that percentage increases in pet visits to veterinary clinics increase linearly in $PM_{2.5}$, providing an estimate that can be translated into a concentration-response function necessary to quantify the benefits of air quality improvements Goodkind, Coggins and Marshall (2014); Pope et al. (2015). Further work is needed to better characterize the pet health – air pollution relationship for other health endpoints, including premature mortality. Ultimately, this growing body of evidence will support rigorous cost-benefit analyses of policies aimed at enhancing animal well-being, including that of companion animals Sunstein (2024); Budolfson et al. (2024). In addition, further empirical evidence on pet health impacts may increase the salience of air pollution and other risks to pet health and change pet owner behavior.[6]

government investigation into the vetcare sector (Competition and Markets Authority, 2024), we estimate an approximate journey time by car of 10 minutes. Assuming an average visit duration of 1 hour gives us a total time of 80 minutes. Using UK government guidance for travel costs via personal car and the value of time (UK Department for Transport, 2025), we compute an avoided time and travel cost of 12 pounds per visit.

[6]For example, the American Veterinary Medical Association released specific guidelines to alert pet owners to protect their pets from the deleterious effects of wildfire smoke (American Veterinary Medical Association,

Our research design faces several challenges and we want to acknowledge its limitations. First, daily average fine particulate concentration levels are highly autocorrelated: high pollution levels on one day are likely to be followed by higher levels on the following day. To assuage this concern, we utilize weekly average $PM_{2.5}$ levels and the same quasi-experimental methods used in recent studies of air pollution and human health (e.g., Deryugina et al., 2019; Sager, 2019; Chen, Oliva and Zhang, 2022). Nevertheless, SI Table S10—which presents estimated effects of weekly lags and leads of air pollution on vet visits—illustrates that autocorrelation in $PM_{2.5}$ may limit the extent to which we can interpret our primary estimates as reflecting the effects of solely last week's pollution.

Second, $PM_{2.5}$ concentration levels are also correlated with the concentration levels of other air pollutants such as ozone and sulfur dioxide. For example, among other pollutants, burning coal emits sulfur dioxide, nitrogen oxides, and fine particulate matter (Jaramillo and Muller, 2016). This "multi-pollutant" problem can make it challenging to isolate the causal impacts of fine particulate matter on human and animal health (Dominici et al., 2010).

Third, while we study the relationship between $PM_{2.5}$ and vet visits, we are limited in our ability to identify the exact physiological pathways that underpin these changes in vetcare utilization. More detailed data on the illnesses pets experience and the exact treatments provided could help shed further light on these pathways. Measuring the effects of air pollution on pet mortality—ideally using data comparable to the human vital statistics datasets employed in prior studies—would also be of significant interest, if such data are available.

2025).

Finally, our analysis measures air pollution exposure using nearby readings of ambient outdoor air pollution. However, humans spend the majority of their time indoors. Indoor air quality is thus a key determinant of overall $PM_{2.5}$ exposure World Health Organization (2014); Organization (2021). The same is true for pets, especially pets that remain exclusively indoors. While indoor and outdoor air quality are correlated, the two can diverge depending on building ventilation, air purification, and indoor sources of pollution such as cooking and heating Roth (2015).

Our focus on ambient air quality mirrors the existing research on human health, the vast majority of which also uses ambient outdoor measures of air quality Roth (2015). This is driven in part by the availability of data — pollution monitor and satellite derived measures of air quality are widely available whereas data from indoor pollution monitors are not. While our findings provide important new insights on the impact of air quality on animal health, further research that focuses on the impacts of indoor air quality would be valuable.

4 Data and Methods

4.1 Data

The empirical analysis leverages daily visit-level data from veterinary practices across the United Kingdom over the period January 2017 to September 2022. The data are taken from the Small Animal Veterinary Surveillance Network (SAVSNET) database, which is administered by the University of Liverpool. The database includes visit information from around 10% of the five thousand veterinary practices in the UK. A more detailed description of SAVSNET can be found in Sánchez-Vizcaíno et al. (2015). We provide additional detail on the SAVSNET data in SI Appendix A.

For each consultation/visit, the data include unique IDs for the veterinary practice and the pet, the species of the pet, age group, sex, the date and time of the visit, location of the practice at the NUTS3 region level (similar in granularity to U.S. counties), and the practitioner-derived main presenting complaint.[7] We focus on cats and dogs, the two species that make up the bulk of vet visits. The resulting estimation sample contains data on approximately 3.8 million unique cats and dogs.[8] We have 1.9 million visits for cats and 5 million visits for dogs.

We combine the vet visits data with hourly readings from air pollution monitors across the United Kingdom from UK Air, accessed via Openair Carslaw and Ropkins (2012). The locations of the air quality monitors in the sample and figures presenting the geographic variation in average $PM_{2.5}$ concentration levels in the sample are shown in SI Appendix A. We calculate air pollution levels first for each of the almost 10,000 Middle Layer Super Output Areas (MSOAs) in the UK. These are census geographies each with a population of approximately 7,000 people (similar to US census tracts). For each MSOA, we take the inverse distance weighted average of the three nearest pollution monitors within 50km of the centroid of the area.[9] We then calculate NUTS3 region level average pollution by taking the

[7]Information on pet owners, including residential address and income, are not available.

[8]Many pets only visit the vet 1-2 times. For this reason, we lack the statistical power to consider models reliant on within-pet variation in air pollution levels.

[9]Since we do not observe residential addresses of pet owners, we are implicitly assuming that pet owners rely on veterinary practices located in the same NUTS3 region as their residences.

population-weighted average across all the MSOAs in each region. Full details can be found in SI Appendix A.

In summary, we construct a panel data set to study the effect of weekly average ambient $PM_{2.5}$ concentration levels on the daily number of veterinary practices visits in each NUTS3 region. Importantly, the longitudinal nature of the database allows us to eliminate the confounding effect of time-invariant unobserved determinants of pet health in each region (such as average economic status and long-term spatial differences in air pollution levels), and unobserved time-varying factors that are common across regions (such as recessions and nationwide reductions in air pollution levels).

We also control for daily temperature and precipitation in the empirical specifications, as weather can impact animal health and pet owners' decisions to visit a veterinary practice. We compile hourly data on temperature and other meteorological variables from the ERA-5 reanalysis dataset, which provides consistent global estimates on a $0.25° \times 0.25°$ grid (resolution of approximately 25-30km) Hersbach et al. (2023). In addition to controlling for weather in the models underlying the primary empirical analysis, we also use the weather data to identify the presence of thermal inversions and wind direction. In robustness checks, we employ both thermal inversions and wind direction as instrumental variables to generate exogenous variation in ambient $PM_{2.5}$ levels.

Table 2 provides summary statistics. The estimation sample contains roughly 1.9 million visits for cats and 5 million visits for dogs. Cats exhibit an older age distribution than dogs, reflecting their longer average lifetimes. When breaking visits out by the "Main Presenting Complaint" (MPC) that is recorded in the vet notes, the most common type of visit is for

Table 2: Summary Statistics for Vet Visits

	Cat	Dog
Sex: Female	0.510	0.487
Age: 0-4	0.320	0.371
Age: 12-16	0.177	0.113
Age: 16+	0.089	0.006
Age: 4-8	0.208	0.263
Age: 8-12	0.206	0.247
MPC: Gastroenteric	0.020	0.031
MPC: Kidney Disease	0.008	0.003
MPC: Other Healthy	0.264	0.276
MPC: Other Unwell	0.202	0.194
MPC: Post-Op	0.062	0.074
MPC: Pruritus	0.023	0.051
MPC: Respiratory	0.012	0.009
MPC: Trauma	0.045	0.043
MPC: Tumour	0.011	0.018
MPC: Unknown	0.002	0.002
MPC: Vaccination	0.350	0.299
N	1861334	4960176

Notes: This table contains summary statistics on pet veterinary visits data. An observation is a unique vet consultation event. All variables shown are indicator variables and the values shown are the means across the sample. MPC stands for "Main Presenting Complaint".

"Vaccination", comprising 31% of visits. Another 47% of visits fall into the broad categories of "Other Healthy" and "Other Unwell". The remainder of visits are made up of a variety of more granular categories related to issues such as "Trauma", "Post-Op", "Kidney Disease" and so on. Visits classified with a Main Presenting Complaint of "Respiratory" comprise only around 1% of visits.

4.2 Methods

The goal of the empirical analysis is to determine whether there is a relationship between local air quality and the frequency of vet visits. We therefore aggregate the visit-level data to obtain a daily count of visits by species for each NUTS3 geographic region. Information on sex and age group bin are converted to shares. We do this by dividing the count of visits for each sex or age group category for a given day and region by total all-cause visits for the same day and region. We also conduct versions of the analysis where we examine counts of visits for a specific main presenting complaint.

Since the number of visits to a vet clinic is a count variable, we use a panel Poisson regression model relating the daily total number of visits in a NUTS3 region ($N_{i,t}$) to daily average $\text{PM}_{2.5}$ concentration levels:[10]

$$log(E[N_{i,t}|Z_{i,t}]) = \alpha_i + \theta_t + \beta \text{PM2.5}_{i,t} + \gamma X_{i,t} \tag{1}$$

[10] Poisson regression generates consistent estimates of the coefficients and clustered standard errors even if the underlying data are not Poisson distributed—so long as $E[Y_{i,t}|X_{i,t}] = exp(X_{i,t}\beta)$ (Wooldridge, 1999). We thus prefer the Poisson regression specification even in the presence of overdispersion in our vet visit data. Nevertheless, we present sensitivity analysis in which we estimate our primary specification via negative binomial regression in Table S11.

for each NUTS3 region i and day t. We include age, sex, and weather controls ($X_{i,t}$), as well as NUTS3 fixed effects (α_i) and day-of-sample fixed effects (θ_t) in all specifications. The NUTS3 region fixed effects control for all time-invariant counfounders that vary at the NUTS3 region level (e.g., persistent differences in socioeconomic status across region). The day-of-sample fixed effect control for unobserved time-varying confounders that are common across all NUTS3 regions (e.g., seasonality of vet visits and overall economic trends). The weather controls include precipitation and 2°C bins of temperature. We weight our regressions by the population of each NUTS3 region to ensure that the sample is more representative of the geographic distribution of the population of pets.[11]

The weather controls are relevant not just to account for their direct effect on pet health, but also to control for their role in determining pet owners' decisions to take their pet to the vet. For instance, we observe a reduction in vet admissions on very hot or very cold days, suggesting that pet owners are less likely to take their pet to the vet on those days. Pet owners may also avoid vet visits on high pollution days, depending on the salience of air pollution and its health effects. Consequently, our estimated effects of air pollution on vet visits should be interpreted as being net of this avoidance behavior.

The primary independent variable of interest is daily regional fine particulate concentration levels (i.e, $PM2.5_{i,t}$). Consistent with other studies on air pollution, we do not just focus on air pollution on the day of visit Deryugina et al. (2019). Instead, in our preferred specification, we consider rolling averages of $PM2.5_{i,t}$ in order to better measure sustained recent exposure to poor air quality. Namely, in equation (1), we define $PM2.5_{i,t}$ as the rolling

[11]This assumes that pets are distributed proportionally with the human population.

average of daily PM2.5 over a seven-day period ending with day t. In SI Appendix C, we also consider models based only on contemporaneous exposure (i.e., the relationship between vet visits on date t and $PM_{2.5}$ on date t only). The estimated effects are noisier and smaller in magnitude than those reported in Table 1. This suggests that our main estimates are not inflated by short-term displacement effects Deryugina et al. (2019).

Regressions are estimated separately for each species $s \in \{\text{cat}, \text{dog}\}$ and outcome variable (i.e., all cause admissions, admissions by main presenting complaint, and admissions by age group). Standard errors are clustered by NUTS3 region to account for autocorrelation in the error term across days within each geographic area.

As a robustness check, we also consider an instrumental variables approach in which $PM_{2.5}$ levels are instrumented with thermal inversions and wind direction. Both thermal inversions and wind direction are widely employed as instruments for air pollution Deryugina et al. (2019); Sager (2019); Chen, Oliva and Zhang (2022). These meteorological phenomena can generate large fluctuations in air pollution exposure. Indeed, in our case, thermal inversions and wind direction are strong predictors of ambient $PM_{2.5}$, even conditional on the controls and fixed effects. These fluctuations are unlikely to be directly related to pet healthcare decisions, except through their effect on air quality—a necessary assumption to interpret estimates from the IV framework as causal. Our instruments are constructed using ERA-5 reanalysis weather data. Further details on the instrumental variables framework can be found in the SI Appendix D.

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Supplementary Appendix

A Further Detail on Data Used

The primary data used for the empirical analysis is visit-level electronic health records from veterinary practices across the United Kingdom. The data are taken from the Small Animal Veterinary Surveillance Network (SAVSNET) database, which is administered by the University of Liverpool. Practice participation is voluntary and relies on practices using a compatible version of practice management software (Sánchez-Vizcaíno et al., 2015).[1] Pet owners can also choose to opt-out at the time of the consultation.

The voluntary nature of the database means that SAVSNET cannot definitively be viewed as a representative sample. However, the practices that participate do still represent a broad cross-section of veterinary practices across the UK. The significant majority are general veterinary practices, with more specialized or emergency practices making up a much smaller part of the sample. Overall, the database includes visit information from around 10% of the five thousand veterinary practices spread across the UK, making it one of the largest repositories of animal electronic health records available for use in academic research.

The left panel of Figure A.1 shows the average daily number of vet visits we observe in the sample. We have data from a selection of veterinary practices in almost all NUTS3 regions. Coverage is uneven, with some parts of the country more heavily represented than others. This simply reflects the makeup of the vet practices that the team at the University of Liv-

[1]This includes three of the most common vet practice management software vendors in the UK: Premvet, Robovet and Teleos.

erpool have managed to recruit into providing data to the SAVSNET program. One notable area where there is more limited participation (in per capita terms) is in London. This is likely due to the VetCompass database, maintained by the Royal Veterinary College, which has a much greater coverage of veterinary practices in London.[m] Importantly though, SAVSNET retains significant coverage in other key urban areas, such as Birmingham, Manchester, Sheffield, Cardiff, Glasgow, and Edinburgh.

The red dots in the left panel of Figure A.1 represent the air pollution monitors from which we collect data. These comprise the core set of pollution monitors maintained by the UK government. The monitors collect pollution readings every hour on a wide range of pollutants. Monitors are spread across the country and tend to be sited near urban centers where people live. We only use monitors that have been operating for at least one full year out of our five year sample period, leaving us with approximately one hundred core monitors that we rely on pollution readings from. Importantly, not all NUTS3 regions have a pollution monitor, and many have multiple monitors. We therefore develop an approach to calculating the daily pollution value for a given NUTS3 region by using an average of the nearest monitors.

To estimate daily average pollution for each NUTS3 region we first estimate the daily average pollution for each Middle Layer Super Output Area (MSOA). MSOAs are census geographies in the UK and are broadly similar to US census tracts. There are around 9,500 MSOAs in the UK with an average population of 7,000. For each MSOA we calculate daily pollution using the inverse distance weighted average of the three nearest pollution monitors,

[m] The VetCompass database collects similar visit-level data from around 30% of veterinary practices across the UK. Further details can be found here: `https://www.rvc.ac.uk/vetcompass/about/overview`

as measured by their distance to the centroid of the MSOA. Before averaging, we exclude any monitors in a given day with missing values and monitors more than 50km from the centroid of the MSOA in question. We calculate the NUTS3 region daily pollution values by taking the population-weighted average of the values for every MSOA in a given NUTS3 region, providing there are sufficient nearby monitors for MSOAs comprising at least 25% of the total population in a given NUTS3 region. In practice this only matters for a small number of very sparsely populated areas of the country that do not meaningfully affect the overall analysis.[n] This means each daily observation for a region on average draws on MSOA values with non-missing data from 2.3 nearby monitors, with of observations 80% being reliant on data from two or more monitors. The average distance to the set of nearby monitors is 21km.

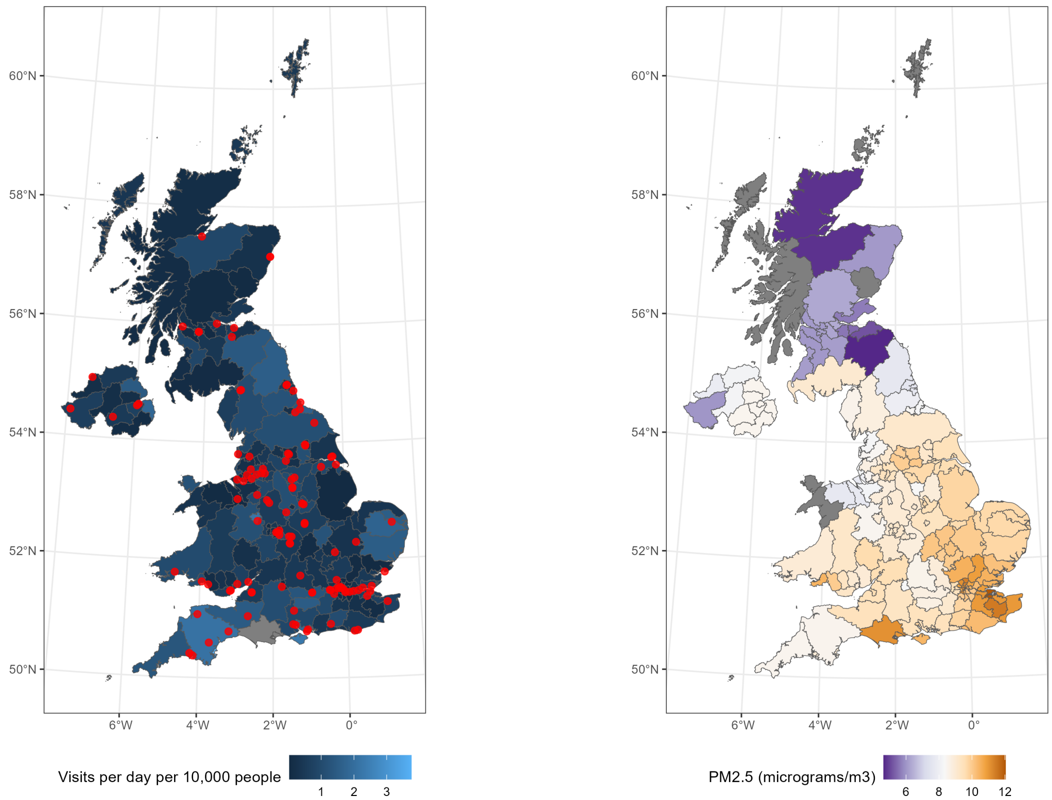
The right panel of Figure A.1 shows the average pollution levels over our sample period for the various NUTS3 regions in the UK. Our main analysis focuses on $PM_{2.5}$, where we can see that pollution levels are higher in central and southern parts of England and Wales. Scotland has the lowest levels of particulate pollution. Our approach to calculating air quality in each NUTS3 region results in us dropping a small portion of the sample located in very rural and sparsely populated parts of the country, as can be seen by the grey areas predominantly located in Scotland and Wales.

Table A.1 shows summary statistics on the visit counts data as used in our regression analysis. Unlike the table in the main text, an observation here is at the NUTS3 region by date level. For certain variables both the contemporaneous daily and average weekly values are shown, consistent with the variables used in our regression analysis.

[n] Of the 174 NUTS3 regions in our analysis, 140 have sufficiently close monitor data for MSOAs covering more than 90% of their population, and only 2 fall below the threshold.

As well as our main dependent variable (all-cause visits) and independent variable ($PM_{2.5}$), the table also includes our two main instruments (thermal inversions and wind direction). Further detail on how these are constructed can be found in SI Section D.

Figure A.1: Maps of pollution monitoring sites and region-specific average $PM_{2.5}$ levels



Notes: This figure plots the location of vet visits in our sample, as well as the different pollution monitoring sites used and average pollution levels. The regions plotted are the NUTS3 regions included in our pet visit data. In the left plot, each region is shaded according to the average daily number of vet visits over the sample period. In the right figure, each region is shaded according to the average level of $PM_{2.5}$ over the sample period.

Table A.1: Summary Statistics on Visit Counts

Variable	N	Mean	Std.Dev.	Min	Median	Max
All-Cause Number of Visits	784378	8.56	17.32	0	1	301
PM 2.5	723614	9.04	6.73	0	7.01	98.7
PM 2.5 (Weekly)	717576	9.03	4.92	1.12	7.74	56.2
IV Inversion Temperature Gradient	771232	-5.03	1.91	-8.38	-5.55	8.58
IV Inversion Temperature Gradient (Weekly)	769120	-5.03	1.3	-7.85	-5.35	3.29
IV East-West Wind Direction	771232	0.33	0.47	0	0	1
IV East-West Wind Direction (Weekly)	769120	0.33	0.3	0	0.29	1
Average Temperature (C)	771232	10.56	5.07	-7.99	10.36	30.23

Notes: This table contains summary statistics on the visit counts data as used in our regression analysis. An observation is a region-by-date. The mean, standard deviation, minimum, median and maximum is shown for each variable. Variables denoted "weekly" are based on the rolling seven-day average for the day in question and the six days preceding.

B Further Detail on Main Specifications

Here we provide additional detail on the results shown in the figures in the main text. Table B.2 provides additional detail on the results by main presenting complaint. Table B.3 provide additional detail on the results by age group.

Table B.2: Estimated effects of daily average $PM_{2.5}$ on vet visits by main presenting complaint

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	0.0004	0.0122***	0.0051	0.0064	0.0022	0.0074*
	(0.0065)	(0.0046)	(0.0041)	(0.0053)	(0.0060)	(0.0042)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Cat	Cat	Cat	Cat	Cat	Cat
IV	No	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.0706	1.034	1.346	0.2383	0.3318	1.788
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	297,016	349,978	351,272	337,960	337,026	351,710
Squared Correlation	0.15325	0.62861	0.64522	0.40475	0.43536	0.72213
Pseudo R^2	0.18910	-0.21776	-0.86027	0.23729	0.20652	-5.0241
BIC	5.96×10^{10}	3.08×10^{11}	3.58×10^{11}	1.4×10^{11}	1.7×10^{11}	3.86×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	0.0034	0.0121***	0.0052	0.0067*	0.0075	0.0064
	(0.0051)	(0.0041)	(0.0037)	(0.0040)	(0.0066)	(0.0044)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Dog	Dog	Dog	Dog	Dog	Dog
IV	No	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.1285	2.612	3.708	0.5787	1.006	4.046
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	332,335	355,538	355,703	354,694	352,184	354,354
Squared Correlation	0.22209	0.69088	0.70469	0.55451	0.61728	0.77148
Pseudo R^2	0.20308	3.4012	1.7242	0.11313	-0.21760	1.5598
BIC	9.56×10^{10}	5.01×10^{11}	5.95×10^{11}	2.36×10^{11}	3.11×10^{11}	5.71×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by main presenting complaint. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level

Table B.3: Estimated effects of daily average $PM_{2.5}$ on vet visits by age group

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0054	0.0077*	0.0083*	0.0086**	0.0089**
	(0.0048)	(0.0045)	(0.0043)	(0.0043)	(0.0038)
Age Group	0	1-4	5-8	9-12	13+
Species	Cat	Cat	Cat	Cat	Cat
IV	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.7285	1.184	1.080	1.030	1.110
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	345,759	352,234	347,199	351,411	349,311
Squared Correlation	0.59234	0.71837	0.71530	0.71546	0.74252
Pseudo R^2	0.18664	-0.21077	-0.07138	-0.01711	-0.10849
BIC	2.18×10^{11}	2.77×10^{11}	2.61×10^{11}	2.55×10^{11}	2.63×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0068*	0.0071*	0.0072*	0.0075**	0.0078**
	(0.0039)	(0.0038)	(0.0039)	(0.0037)	(0.0038)
Age Group	0	1-4	5-8	9-12	13+
Species	Dog	Dog	Dog	Dog	Dog
IV	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.941	3.929	3.559	3.050	0.9811
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	355,368	355,705	355,705	355,705	355,537
Squared Correlation	0.73825	0.81196	0.80890	0.80378	0.62197
Pseudo R^2	-10.482	1.5315	1.6608	1.9799	0.01719
BIC	3.61×10^{11}	5.04×10^{11}	4.74×10^{11}	4.37×10^{11}	2.57×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by age group. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

C Further Detail on Contemporaneous vs Weekly Average Pollution

All of our results focus on pollution as measured by a rolling average over a seven-day period ending with day t. We do this as it seems unlikely that very short-term fluctuations in air quality would lead to a notable increase in vet visits on the same day. However, as a sensitivity analysis, we estimate the same specifications using contemporaneous daily measures of ambient $PM_{2.5}$ instead.

For all-cause visits, we estimate an effect of 0.24% for cats and 0.22% for dogs. These estimated effects of contemporaneous daily ambient $PM_{2.5}$ on all-cause visits are not statistically significant at the 5% level.

For visits by main presenting complaint, we find that visits classified as "Other Unwell" again have the clearest positive response, with an effect of 0.38% for cats and 0.37% for dogs. Both of these effects are statistically significant at the 5% level. The estimated effects for all other visit types are small and are not statistically significant, with the exception of vaccinations for cats which does now see a significant effect.

For visits by age group, we observe a slight increase in estimated effect sizes as age increases, but with no statistically significant differences across ages.

Therefore, our results using contemporaneous daily ambient $PM_{2.5}$ produce qualitatively similar findings to our main results using a rolling average of ambient $PM_{2.5}$ over a seven-day period ending with day t. The smaller effect sizes are consistent with the reliance on same-day fluctuations in pollution exposure. This also reduces statistical power, which explains the lower level of statistical significance for the results.

Table C.4: Estimated effects of daily average $PM_{2.5}$ on all-cause vet visits

Model:	(1)	(2)	(3)	(4)
Variables				
PM2.5	0.0024*	0.0022*	0.0045*	0.0011
	(0.0013)	(0.0013)	(0.0025)	(0.0023)
Species	Cat	Dog	Cat	Dog
IV	No	No	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.040	13.45	5.040	13.45
Fixed-effects				
NUTS3 Area	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	358,717	358,887	358,717	358,887
Squared Correlation	0.82308	0.84131	0.82308	0.84131
Pseudo R^2	1.3462	1.1121	1.3462	1.1121
BIC	6.25×10^{11}	1.05×10^{12}	6.25×10^{11}	1.05×10^{12}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is also daily. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We also estimate regression specifications instrumenting for air pollution using wind direction and thermal inversion events (Columns 3-4). We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

Table C.5: Estimated effects of daily average $PM_{2.5}$ on vet visits by main presenting complaint

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	-0.0017	0.0038**	0.0016	0.0002	-0.0006	0.0035**
	(0.0033)	(0.0015)	(0.0016)	(0.0020)	(0.0026)	(0.0015)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Cat	Cat	Cat	Cat	Cat	Cat
IV	No	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.0706	1.035	1.344	0.2382	0.3321	1.787
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	299,551	352,784	354,128	340,723	339,647	354,505
Squared Correlation	0.15316	0.62795	0.64490	0.40431	0.43493	0.72180
Pseudo R^2	0.18921	-0.21967	-0.85862	0.23720	0.20618	-5.0355
BIC	6×10^{10}	3.1×10^{11}	3.6×10^{11}	1.41×10^{11}	1.71×10^{11}	3.89×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	0.0020	0.0037**	0.0013	0.0021	0.0029	0.0022
	(0.0024)	(0.0015)	(0.0014)	(0.0017)	(0.0027)	(0.0017)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Dog	Dog	Dog	Dog	Dog	Dog
IV	No	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.1288	2.613	3.705	0.5787	1.008	4.046
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	334,993	358,548	358,717	357,701	355,068	357,364
Squared Correlation	0.22237	0.68985	0.70374	0.55389	0.61571	0.77089
Pseudo R^2	0.20312	3.3955	1.7260	0.11282	-0.21974	1.5599
BIC	9.62×10^{10}	5.05×10^{11}	6×10^{11}	2.38×10^{11}	3.14×10^{11}	5.75×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by main presenting complaint. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is also daily. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

Table C.6: Estimated effects of daily average $PM_{2.5}$ on vet visits by age group

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0022	0.0026	0.0030**	0.0027	0.0030**
	(0.0017)	(0.0017)	(0.0015)	(0.0017)	(0.0012)
Age Group	0	1-4	5-8	9-12	13+
Species	Cat	Cat	Cat	Cat	Cat
IV	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.7284	1.184	1.080	1.029	1.110
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	348,677	355,072	349,999	354,291	352,117
Squared Correlation	0.59150	0.71787	0.71489	0.71470	0.74186
Pseudo R^2	0.18624	-0.21232	-0.07201	-0.01762	-0.10903
BIC	2.19×10^{11}	2.79×10^{11}	2.62×10^{11}	2.57×10^{11}	2.65×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0022	0.0023	0.0024	0.0020	0.0027*
	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0015)
Age Group	0	1-4	5-8	9-12	13+
Species	Dog	Dog	Dog	Dog	Dog
IV	No	No	No	No	No
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.942	3.930	3.559	3.050	0.9806
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	358,378	358,718	358,718	358,717	358,549
Squared Correlation	0.73773	0.81096	0.80807	0.80282	0.62049
Pseudo R^2	-10.691	1.5320	1.6615	1.9813	0.01710
BIC	3.64×10^{11}	5.08×10^{11}	4.77×10^{11}	4.4×10^{11}	2.59×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by age group. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is also daily. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

D Further Detail on Instrumental Variables Specifications

D.1 Further Detail on Instrumental Variables Methods

To further address concerns about unobserved local factors correlated with $PM_{2.5}$ and vet visits, we consider an instrumental variables approach. An instrumental variables approach can also help mitigate concerns about measurement error. This is of particular relevance to our measure of pollution which necessarily cannot perfectly capture the pollution levels that each individual pet in our sample is exposed to.

Here, we instrument for $PM_{2.5}$ using both thermal inversions and wind direction. These are both commonly used instruments that provide sources of variation in air pollution that are driven by weather factors that are themselves unlikely to be directly related to the pet healthcare decisions of interest, except through their effect on air pollution (Deryugina et al., 2019; Sager, 2019; Chen, Oliva and Zhang, 2022).

To construct a measure of thermal inversions, we use reanalysis weather data from ERA-5. These data provide temperature values at both ground level and at varying altitudes (pressure levels). We construct a continuous instrument by calculating the difference between the temperature at 1000m (900hpa) and the temperature nearer the surface at 100m (1000hpa). We then create a binary version of the instrument that takes a value of one when this difference is positive, and zero otherwise, yielding inversions on 3% of the days in our sample.

To construct a measure of wind direction, we again use the reanalysis weather data from ERA-5 which provides wind direction values. These values range from 0 to 360 degrees clockwise from north. The prevailing wind direction in the UK blows in off the Atlantic from west to east. Air pollution carried by the wind is highest when the wind reverses direction and blows from east to west. During these periods, air pollution is blown to the UK from Continental Europe. We therefore construct a binary instrument that takes a value of one when the wind direction is between 0 and 180 degrees (clockwise from north), and zero otherwise, yielding reverse wind direction on 33% of the days in our sample.

Our two instruments have a strong first stage with a Wald F-statistic of 207.[o] Consistent with other studies, we use the continuous version of the thermal inversion temperature difference as it produces a stronger first stage than the binary version of the instrument.[p]

One challenge of implementing an instrumental variables approach in our setting is doing so using our Poisson specification and rich set of fixed effects. Hence, we must bootstrap the standard errors. We conduct the estimation by fitting the first stage with our two instruments and the same controls and fixed effects included in our main specification. We then save the residuals from this first stage regression and include them as controls in our second stage main Poisson specification. We repeat for five hundred random bootstrap samples of our dataset, storing the coefficients each time in order to calculate the final standard errors.

[o]Each instrument separately also has a strong first stage with an F-statistic of the same order of magnitude.

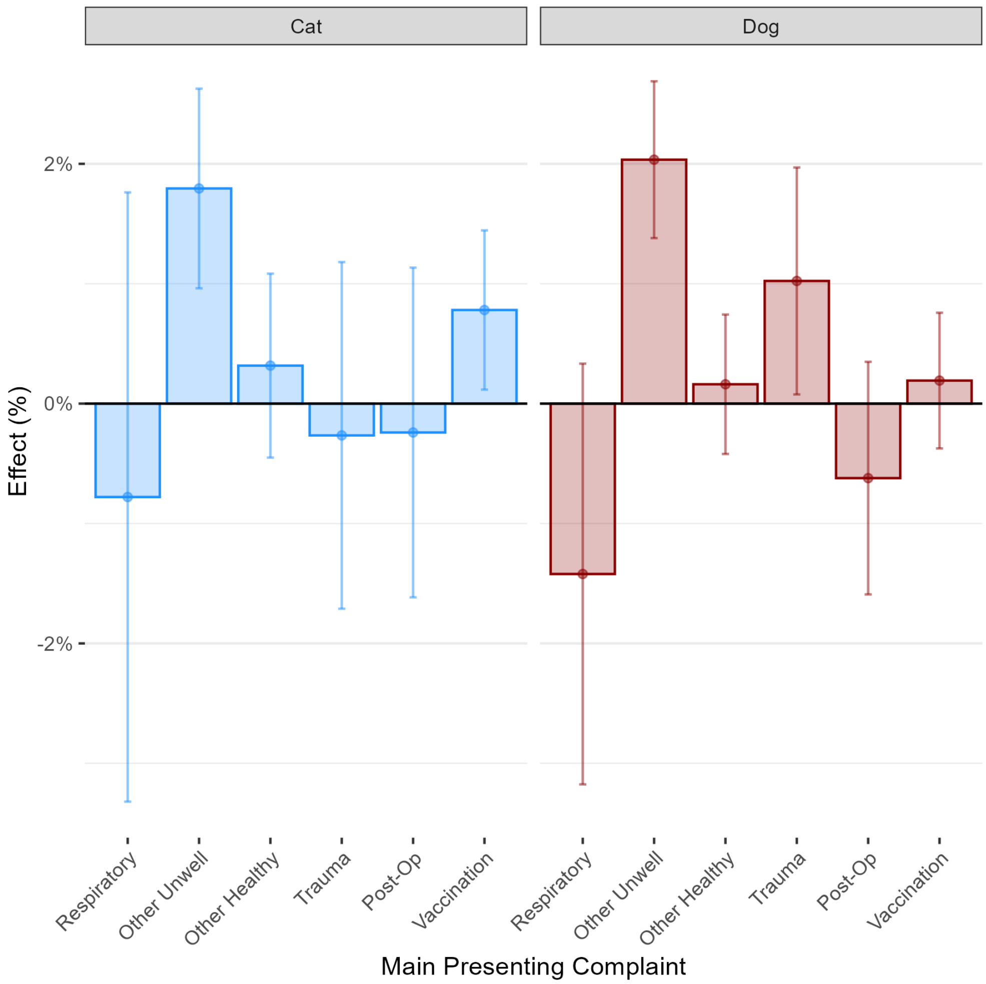
[p]For the binary thermal inversions instrument, the first stage Wald F-statistic is 28.

D.2 Further Detail on Instrumental Variables Results

Figure D.2 and Table D.7 presents the results for visits by main presenting complaint estimated using instrumental variables. The effects for visits classed as “Other Unwell” are of particular interest given the results in the main text. Here, we see the coefficient estimates for both cats and dogs are slightly larger than those found in the main text using a fixed effects approach. We do also see small, statistically significant effects in the “Vaccination” category for cats and the “Trauma” category dogs, while all other visit categories continue to show no statistically significant effects. Importantly, the effect sizes for “Other Unwell” continue to be the largest and most significant for any of the categories of main presenting complaint.

Figure D.3 and Table D.8 also presents the results for all-cause visits by age group estimated using instrumental variables. The effect sizes remain broadly comparable to those in the main specification, although they are noisier with less of a clear stable pattern across age groups.

Figure D.2: IV estimated effects of $PM_{2.5}$ on vet visits by main presenting complaint



Notes: This figure presents estimates and 95% confidence intervals from instrumental variables Poisson regressions of the impact of $PM_{2.5}$ concentration levels on the count of vet visits by main presenting complaint. The measure of air pollution used is daily values for the rolling weekly average up to that day. We construct instruments for $PM_{2.5}$ based on both wind direction and thermal inversion. All regressions include controls for pet age, sex, and various weather controls, as well as NUTS3 and day-of-sample fixed effects. We estimate separate Poisson regressions for each species and for each main presenting complaint. We weight our regressions by the population of each NUTS3 region. Standard errors are computed via a NUTS3-region-level cluster bootstrap.

Table D.7: IV estimated effects of $PM_{2.5}$ on vet visits by main presenting complaint

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	-0.0142	0.0204***	0.0016	0.0102**	-0.0062	0.0019
	(0.0090)	(0.0033)	(0.0030)	(0.0048)	(0.0050)	(0.0029)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Dog	Dog	Dog	Dog	Dog	Dog
IV	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.1285	2.612	3.708	0.5787	1.006	4.046
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	332,335	355,538	355,703	354,694	352,184	354,354
Squared Correlation	0.22210	0.69090	0.70470	0.55451	0.61726	0.77148
Pseudo R^2	0.20309	3.4012	1.7242	0.11313	-0.21759	1.5598
BIC	9.56×10^{10}	5.01×10^{11}	5.95×10^{11}	2.36×10^{11}	3.11×10^{11}	5.71×10^{11}

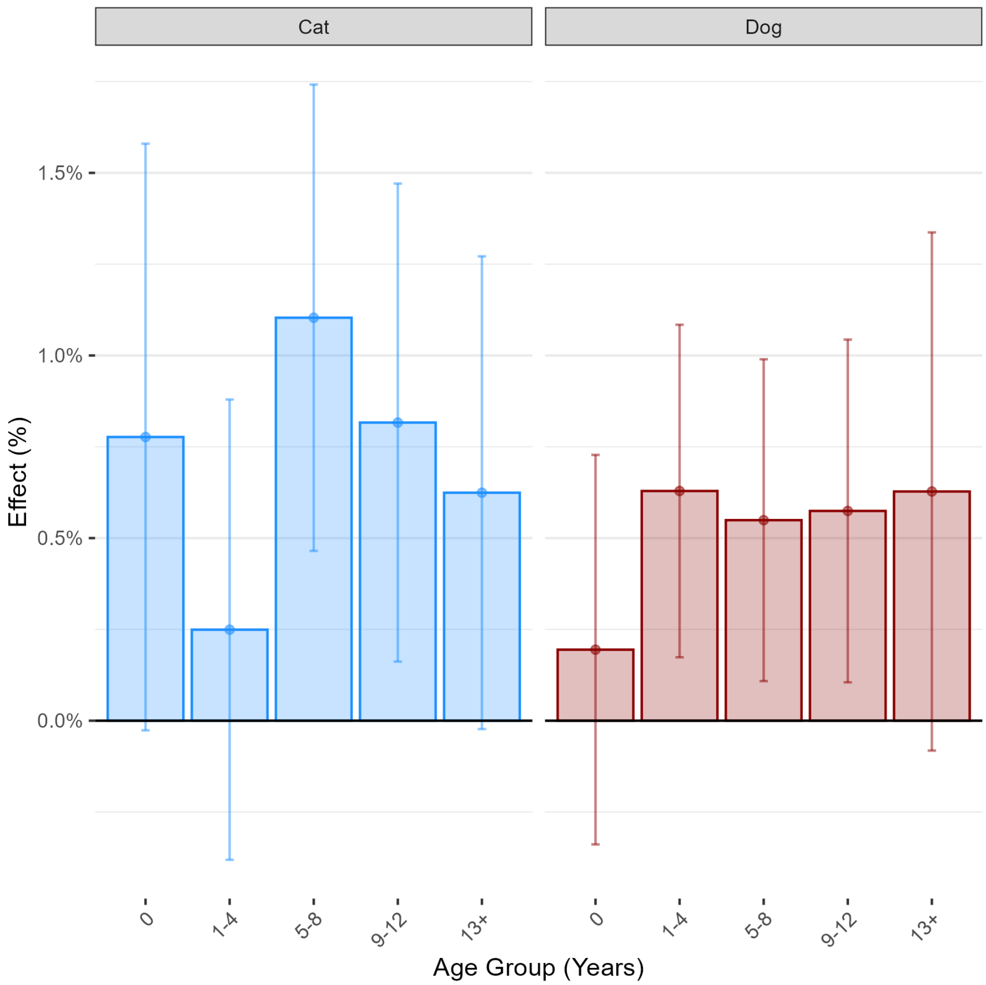
Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PM2.5	-0.0078	0.0180***	0.0032	-0.0027	-0.0024	0.0078**
	(0.0130)	(0.0042)	(0.0039)	(0.0074)	(0.0070)	(0.0034)
MPC	Respiratory	Other Unwell	Other Healthy	Trauma	Post-Op	Vaccination
Species	Cat	Cat	Cat	Cat	Cat	Cat
IV	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.0706	1.034	1.346	0.2383	0.3318	1.788
Fixed-effects						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	297,016	349,978	351,272	337,960	337,026	351,710
Squared Correlation	0.15324	0.62863	0.64523	0.40474	0.43535	0.72213
Pseudo R^2	0.18910	-0.21776	-0.86026	0.23730	0.20652	-5.0241
BIC	5.96×10^{10}	3.08×10^{11}	3.58×10^{11}	1.4×10^{11}	1.7×10^{11}	3.86×10^{11}

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents instrumental variables Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by main presenting complaint. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We instrument for air pollution using wind direction and thermal inversion events. We weight our regressions by the population of each NUTS3 region. Standard errors are computed via a NUTS3-region-level cluster bootstrap.

Figure D.3: IV estimated effects of $PM_{2.5}$ on vet visits by age group



Notes: This figure presents estimates and 95% confidence intervals from instrumental variables Poisson regressions of the impact of $PM_{2.5}$ concentration levels on the count of vet visits by age group. The measure of air pollution used is daily values for the rolling weekly average up to that day. We construct instruments for $PM_{2.5}$ based on both wind direction and thermal inversion. All regressions include controls for pet age, sex, and various weather controls, as well as NUTS3 and day-of-sample fixed effects. We estimate separate Poisson regressions for each species and for each age group. We weight our regressions by the population of each NUTS3 region. Standard errors are computed via a NUTS3-region-level cluster bootstrap.

Table D.8: IV estimated effects of $PM_{2.5}$ on vet visits by age group

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0019	0.0063***	0.0055**	0.0057**	0.0063*
	(0.0027)	(0.0023)	(0.0022)	(0.0024)	(0.0036)
Age Group	0	1-4	5-8	9-12	13+
Species	Dog	Dog	Dog	Dog	Dog
IV	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.941	3.929	3.559	3.050	0.9811
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	355,368	355,705	355,705	355,705	355,537
Squared Correlation	0.73824	0.81196	0.80890	0.80378	0.62197
Pseudo R^2	-10.482	1.5315	1.6608	1.9799	0.01719
BIC	3.61×10^{11}	5.04×10^{11}	4.74×10^{11}	4.37×10^{11}	2.57×10^{11}

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
PM2.5	0.0078*	0.0025	0.0110***	0.0082**	0.0062*
	(0.0041)	(0.0032)	(0.0033)	(0.0033)	(0.0033)
Age Group	0	1-4	5-8	9-12	13+
Species	Cat	Cat	Cat	Cat	Cat
IV	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.7285	1.184	1.080	1.030	1.110
Fixed-effects					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	345,759	352,234	347,199	351,411	349,311
Squared Correlation	0.59235	0.71837	0.71531	0.71546	0.74252
Pseudo R^2	0.18664	-0.21076	-0.07138	-0.01711	-0.10849
BIC	2.18×10^{11}	2.77×10^{11}	2.61×10^{11}	2.55×10^{11}	2.63×10^{11}

Custom standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents instrumental variables Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits by age group. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We instrument for air pollution using wind direction and thermal inversion events. We weight our regressions by the population of each NUTS3 region. Standard errors are computed via a NUTS3-region-level cluster bootstrap.

E Additional Empirical Robustness Checks

E.1 Further Detail on Additional Seasonal Regional Controls

All of our results use a consistent set of unit fixed effects for each NUTS3 region and time fixed effects for each day-of-sample. However, there may be other regional seasonal patterns in air quality and pet health that we may not be adequately controlling for. As such we also examine versions of our specifications with additional richer fixed effects. Here we present results that also include NUTS3 region-by-month fixed effects to allow for different seasonal patterns across regions.

Focusing on our analysis of all-cause visits, Table E.9 indicates that our core qualitative findings remain largely unchanged by the inclusion of additional seasonal regional controls. For our fixed effects regressions, we find very similar effects to our main results, with an effect of 0.72% for cats and 0.77% for dogs. These estimated effects of $PM_{2.5}$ on all-cause visits are both statistically significant at the 5% level. Turning to our instrumental variables approach, for cats the effect remains similar in size and statistically significant. For dogs we see an effect that is smaller in magnitude and now no longer statistically significant.

Table E.9: Estimated effects of daily average $PM_{2.5}$ on vet visits with additional seasonal regional controls

Model:	(1)	(2)	(3)	(4)
Variables				
PM2.5	0.0072^{*}	0.0077^{**}	0.0069^{**}	0.0038
	(0.0041)	(0.0039)	(0.0029)	(0.0023)
Species	Cat	Dog	Cat	Dog
IV	No	No	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.158	13.46	5.158	13.46
Fixed-effects				
NUTS3 Area-month	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	347,725	355,612	347,725	355,612
Squared Correlation	0.82770	0.84686	0.82770	0.84686
Pseudo R^2	1.3372	1.1101	1.3372	1.1101
BIC	6.13×10^{11}	1.02×10^{12}	6.13×10^{11}	1.02×10^{12}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region-by-month and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We also estimate Poisson regression specifications instrumenting for air pollution using wind direction and thermal inversion events (Columns 3-4). We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

E.2 Further Detail on Temporal Dynamics with Lags and Leads

Our main results use weekly average pollution as our independent variable of interest. This captures the relationship between visits on a given day and pollution over the preceding week, including the day in question. However, it may be that pollution can affect visits over time horizons longer than a week. As such, we estimate a modified version of our main specification that includes both lags and leads of our measure of weekly average pollution. Due to the weekly nature of the variable, we include leads and lags up to four weeks before and after the day of interest.

Focusing on our analysis of all-cause visits, Table E.10 shows that the clearest effects on vet visits arise in response to pollution over the preceding week, which is the time horizon we include in our main specification. The effects of pollution in weeks that are much earlier or later than the day of interest are smaller and sometimes not statistically significant.

Even so, the results of these specifications using leads and lags highlight limitations of our research design. While the effects from the preceding week are the clearest and are statistically significant, there are statistically significant effects of meaningful magnitude in both earlier and later weeks. It is possible that the effects of past pollution exposure on vet visits may extend beyond the preceding week. However, it is less plausible that there is a relationship between current vet visits and pollution in future weeks. That we do not see large changes in the magnitude of the coefficients across many of the leads and lags therefore likely reflects the high degree of autocorrelation in air pollution (i.e., air pollution levels are highly correlated over time).

Table E.10: Estimated effects of daily average $PM_{2.5}$ on vet visits with dynamic leads and lags

Model:	(1)	(2)
Variables		
Lead(PM2.5,28)	0.0027	0.0030*
	(0.0019)	(0.0017)
Lead(PM2.5,21)	0.0019	0.0018
	(0.0018)	(0.0016)
Lead(PM2.5,14)	0.0027*	0.0026*
	(0.0015)	(0.0014)
Lead(PM2.5,7)	0.0026**	0.0029**
	(0.0013)	(0.0013)
PM2.5	0.0033**	0.0033***
	(0.0014)	(0.0013)
Lag(PM2.5,7)	0.0035**	0.0029**
	(0.0014)	(0.0013)
Lag(PM2.5,14)	0.0031*	0.0030**
	(0.0017)	(0.0015)
Lag(PM2.5,21)	0.0029*	0.0023
	(0.0017)	(0.0015)
Lag(PM2.5,28)	0.0030	0.0033*
	(0.0024)	(0.0018)
Species	Cat	Dog
IV	No	No
Age Controls	Yes	Yes
Sex Controls	Yes	Yes
Weather Controls	Yes	Yes
Dep. Var. Mean	5.079	13.47
Fixed-effects		
NUTS3 Area	Yes	Yes
Date	Yes	Yes
Fit statistics		
Observations	333,214	334,362
Squared Correlation	0.82767	0.84753
Pseudo R^2	1.3414	1.1101
BIC	5.86×10^{11}	9.74×10^{11}

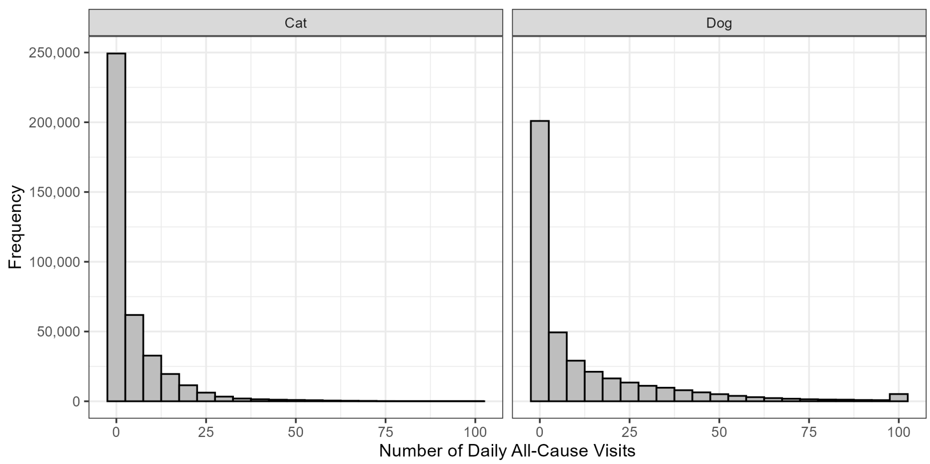
Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents Poisson regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. We include leads and lags of our air pollution measure at 7, 14, 21 and 28 days relative to the visit day in question. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. We also control for lags and leads of the weather controls to match the lags and leads of pollution. Dependent variable means are included in the table. We estimate separate Poisson regressions for each species. We weight our regressions by the population of each NUTS3 region. Standard errors are clustered at the NUTS3 region level.

E.3 Further Detail on Negative Binomial Specifications

Our main specifications consider a Poisson regression model due to the fact that number of visits is a count variable. Figure E.4 shows a histogram of the all-cause visit count data for our region-by-date sample. An alternative approach that can be used for count data is the Negative Binomial regression model. Table E.11 presents our main all-cause regression results, but this time comparing across Poisson and Negative Binomial regression models.

Figure E.4: Histogram of vet visit counts



Notes: This figure presents the distribution of all-cause vet visits for the regression sample. An observation is a NUTS3 region by day-of-sample. Observations with values greater than 100 visits per day are winzorized to 100 for presentational purposes.

Table E.11: Estimated effects of daily average $PM_{2.5}$ on vet visits with negative binomial specification

Model:	(1) Poisson	(2) Poisson	(3) Neg. Bin.	(4) Neg. Bin.
Variables				
PM2.5	0.0078**	0.0077**	0.0070*	0.0040
	(0.0033)	(0.0036)	(0.0039)	(0.0038)
Species	Cat	Dog	Cat	Dog
Negative Binomial	No	No	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.042	13.45	5.042	13.45
Fixed-effects				
NUTS3 Area	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	355,705	355,872	355,705	355,872
Squared Correlation	0.82328	0.84205	0.81536	0.82458
Pseudo R^2	0.69801	0.76927	0.26612	0.21735
BIC	1,430,998.9	2,470,895.2	1,283,392.6	1,828,956.1
Over-dispersion			3.2387	2.2380
Over-dispersion Stat.			147,606.3	641,939.0
Over-dispersion pval.			0×10^{-16}	0×10^{-16}

Clustered (NUTS3 Area) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents regression estimates of the impact of $PM_{2.5}$ concentration levels on vet visits. The dependent variable is the daily count of vet visits in a given NUTS3 region. The measure of air pollution used is daily values for the rolling weekly average up to that day. All regressions include controls for pet age, sex, and weather, as well as NUTS3 region and day-of-sample fixed effects. Dependent variable means are included in the table. We estimate separate regressions for each species. Here we compare specifications using Poisson (Columns 1-2) and Negative Binomial (Columns 3-4). We do not weight our regressions by the population of each NUTS3 region for comparability due to our modeling of negative binomial regression not allowing sample weights. Standard errors are clustered at the NUTS3 region level.