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The Impact of Air Pollution on Petcare Utilization^{*}

Olivier Deschenes[†], Stephen Jarvis[‡], Akshaya Jha[§], and Alan D Radford[¶]

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Abstract

There is a large literature documenting the adverse impacts of air pollution on human health. In contrast, there is a paucity of 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., $\text{PM}_{2.5}$) lead to significant increases in the number of vet visits for both cats and dogs. In aggregate, these estimates indicate that reducing ambient $\text{PM}_{2.5}$ levels to a maximum of $5 \mu\text{g}/\text{m}^3$ as recommended by the World Health Organization would result in eighty thousand fewer vet visits each year (a 0.4% reduction).

JEL Codes: I0, Q51, Q53, Q57

Keywords: Pets, Air Pollution, Animal Health

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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 pollution-caused mortality is exposure to fine particulate matter ([NRC and NAS \(2010\)](#); [Muller, Mendelsohn and Nordhaus \(2011\)](#); [Muller \(2014\)](#)). A large body of empirical evidence documents the link between increased exposure to fine particulate matter and a host of human health outcomes, including emergency department visits, hospitalizations, and premature mortality due to respiratory, cardiovascular, and neurological conditions ([Fuller et al., 2022](#)). By comparison, there is relatively little research on how air pollution impacts animal health, despite humans and animals sharing many of the biological pathways that lead to morbidity and mortality ([Losacco and Perillo, 2017](#)).

Exposure to air pollution in wild animal species depends on physiological traits and on the dispersal of air pollution in natural habitats. However, pets typically share the same environmental exposures as their human companions and are therefore exposed to similar levels of ambient air pollution. This is especially concerning in our context—pet health—given the particular value people place on the well-being of their pets. For example, US residents spent roughly 120 billion dollars on their pets in 2022; the corresponding amount in the UK was approximately 10 billion pounds ([Bloomberg Intelligence, 2023](#); [Office for National Statistics, 2024](#)). The large detrimental effects of air pollution on human health combined with the size of the pet population and the economic resources devoted to their wellbeing motivate the need for a rigorous evaluation of the impact of air pollution on pets.

In this paper, we use visit-level data from an extensive sample of veterinary practices

across the United Kingdom to estimate the impacts of fine particulate exposure (i.e., $\text{PM}_{2.5}$) on the utilization of pet healthcare. Estimates from panel regressions that leverage daily variation in air pollution indicate that increases in $\text{PM}_{2.5}$ concentration levels lead to sizable increases in the number of vet visits for both cats and dogs. A 1 microgram per cubic meter increase in average $\text{PM}_{2.5}$ over the preceding week leads to a 0.7% increase in vet admissions for both cats and dogs.¹ Our effect sizes 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 substantiate the robustness of our findings by showing that the results remain similar when considering instrumental variables specifications that use variation in $\text{PM}_{2.5}$ concentration levels generated by thermal inversions and changes in wind direction ([Deryugina et al., 2019](#); [Sager, 2019](#); [Chen, Oliva and Zhang, 2022](#)). Information on the main presenting complaint for each visit further corroborates that the observed effects are concentrated among visits that could plausibly be driven by poor air quality.

In aggregate, our estimates suggest that reducing ambient $\text{PM}_{2.5}$ levels to a maximum of $5 \mu\text{g}/\text{m}^3$ as recommended by the World Health Organization would lead to eighty thousand fewer vet visits each year (a 0.4% reduction). This entails an annual savings in petcare utilization costs of roughly fifteen million pounds. Importantly, this is only one of the many benefits of reducing air pollution enjoyed by pets and their owners. For example, our annual savings in petcare utilization costs do not encompass reductions in owners' emotional distress, the value of owners' time spent visiting the vet, and increased time spent enjoying

¹Our preferred results use daily rolling averages of pollution during the preceding week. We find similar results using contemporaneous daily pollution, though the estimates are slightly noisier.

companionship due to improved pet lifetimes. The full economic benefits to pet owners of improved air quality are therefore likely to be much higher.

Our paper contributes to the extensive prior literature on the health impacts of air pollution, which has focused almost exclusively on humans. We provide new evidence on the effects for pet dogs and cats. In doing so, our paper contributes to a much smaller literature that studies the impacts of air pollution on animal health. For instance, [Liang et al. \(2020\)](#) documents that reductions in ambient ozone concentration levels led to increased bird abundance in the United States. In terms of effects on companion animals, [Lin et al. \(2018\)](#) estimates the association between indoor air pollution and the health of over three hundred dogs and cats, and [Calderón-Garcidueñas et al. \(2017\)](#) examine potential neurological impacts of air pollution in a sample of twenty-four dogs. Closest to our work, [Giugliano et al. \(2024\)](#) uses large-scale data from the Italian National Canine Registry to examine the relationship between heavy metals pollution and the life expectancy of dogs. Our study provides the first large-scale empirical analysis of the health impacts of air pollution on pets using quasi-experimental methods and data on 3.8 million unique cats and dogs.

Our paper also contributes to the literature on the economic valuation of animals and biodiversity. A growing body of research has explored the economic impacts of changes in the prevalence of a range of wild animal and bird species ([Ferris and Frank, 2021](#); [Frank and Sudarshan, 2023](#)). Increasingly research has examined the direct inherent value that people assign to protecting certain wild species, and even to specific “charismatic” animal individuals ([Richardson and Lewis, 2022](#); [Costello et al., 2023](#)). We contribute to this work on wildlife by providing early evidence on people’s willingness-to-pay to reduce environmental

harms for domesticated and companion animals.

In fact, despite an extensive literature on the economic value of health benefits for humans ([Viscusi and Masterman, 2017](#)), there is little equivalent research on the value people place on the health of their pets ([Budolfson et al., 2024](#); [Sunstein, 2024](#)). [Carlson et al. \(2020\)](#) is the only study that we are aware of that has examined this directly, in their case by estimating a contingent-valuation-based value of statistical dog life. We contribute to this small body of work by measuring the extent to which pet owners take their pets to the vet in response to an important health shock—air pollution exposure. Our estimated effects suggest a non-trivial portion of the benefits of reducing air pollution may come from improvements in pet health.

2 Data

The empirical analysis leverages daily visit-level data from veterinary practices (VPs) 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 5% of the five thousand VPs in the UK. A more detailed description of SAVSNET can be found in [Sánchez-Vizcaíno et al. \(2015\)](#).

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 level (similar in granularity to U.S. counties), and the main

presenting complaint.² We focus on cats and dogs, the two species that make up the bulk of our dataset. The resulting estimation sample contains data on roughly 3.8 million unique cats and dogs.³ 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. The locations of the air quality monitors in our sample and geographic variation in average PM_{2.5} concentration levels over our sample period can be found in Appendix Figures A.1 and A.2. We calculate pollution levels in each NUTS3 region by taking the inverse distance weighted average of the three nearest pollution monitors within 50km of the centroid of each NUTS3 region.⁴

In summary, we construct a panel data set to study the effect of daily average ambient PM_{2.5} concentration levels on the daily number of VP 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).

Our empirical models also control for daily temperature and precipitation, as those can also 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

²Information on pet owners, including residential address and income, are not provided to us.

³Many pets only visit the vet 1-2 times during our sample period. For this reason, we lack the statistical power to consider models reliant on within-pet variation in pollution levels.

⁴Since 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.

reanalysis dataset, which provides consistent global estimates on a 25-30km grid. In addition to controlling for weather, we utilize our 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 1: 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	1,861,334	4,960,176

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

Table 1 provides summary statistics. Our 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

“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 around 1% of visits.

3 Empirical Approach

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 for a given day and NUTS3 region. We also conduct versions of the analysis where we examine counts of visits for a specific main presenting complaint.

Since the outcome variable is a count, we use a panel Poisson regression model relating the daily total number of visits in a NUTS3 region ($N_{i,t}$) to daily average PM_{2.5} concentration levels:

$$\log(E[N_{i,t}|Z_{i,t}]) = \alpha_i + \theta_t + \beta \text{PM}_{2.5_{i,t}} + \gamma X_{i,t} \quad (1)$$

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 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.⁵

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 $PM_{25,i,t}$. Consistent with other studies on air pollution we do not just focus on pollution on a specific day (Deryugina et al., 2019). Instead in our preferred specification we consider rolling averages of $PM_{25,i,t}$ measured in levels, in order to better measure sustained recent exposure to poor air quality. Namely, we consider a rolling average over a seven-day period ending with day t , 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, our results are robust to using contemporaneous daily measures of air quality as well.

Regressions are estimated separately for each species $s \in \{\text{cat}, \text{dog}\}$ and outcome variable (i.e., all cause admissions and admissions by main presenting complaint). Standard errors are clustered by NUTS3 region. We also consider specifications in which we allow the effects of $PM_{2.5}$ exposure on number of visits to vary by age group.

⁵This assumes that pets are distributed proportionally with human population.

As a robustness check, we also consider an instrumental variables approach in which $\text{PM}_{2.5}$ levels are instrumented with thermal inversions and wind direction. Both thermal inversions and wind direction are widely employed as instruments for air pollution since these plausibly quasi-random meteorological phenomena can generate large fluctuations in air pollution exposure (Deryugina et al., 2019; Sager, 2019; Chen, Oliva and Zhang, 2022). Full details on the results from the instrumental variables framework can be found in the appendix.

4 Results

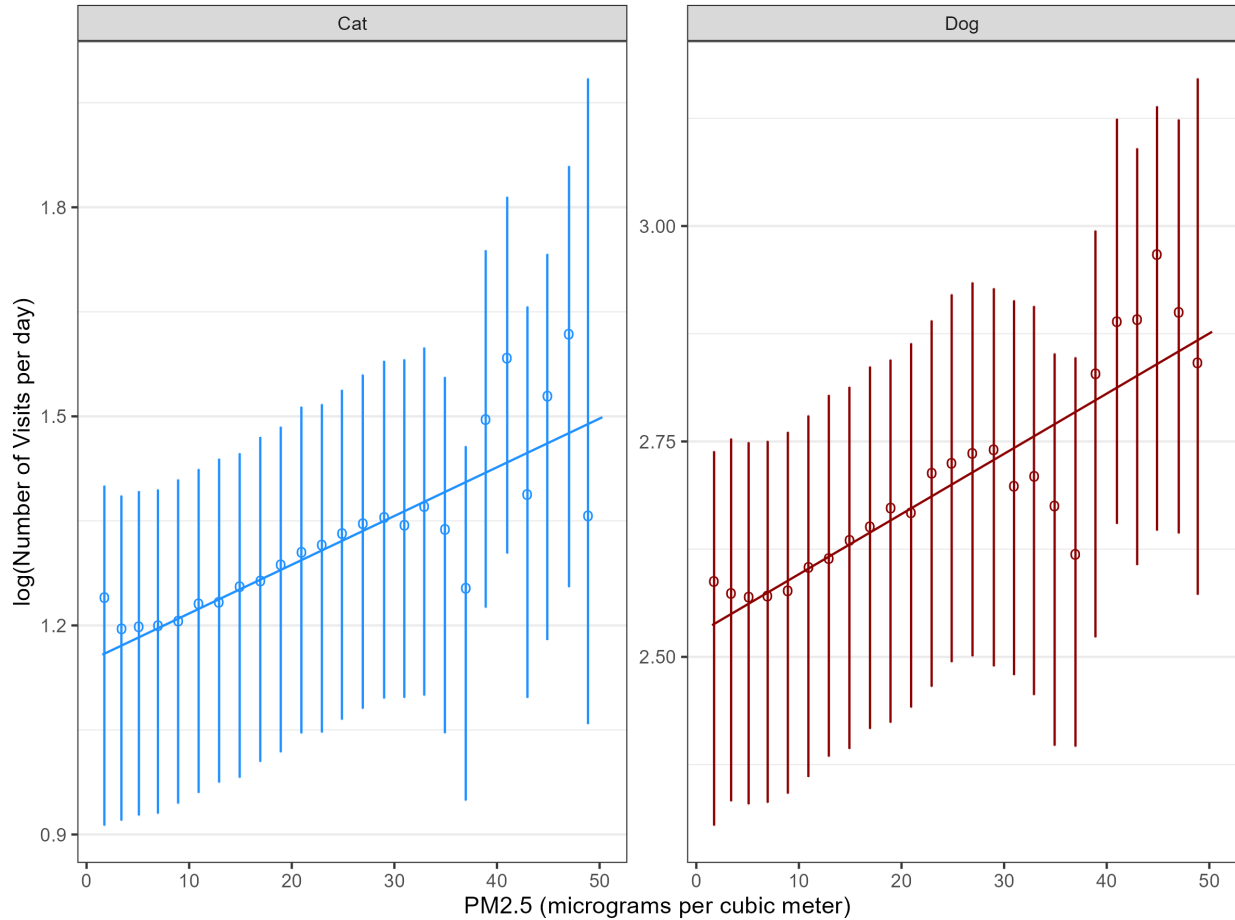
4.1 All-Cause Vet Visits

Figure 1 presents estimates of the effect of $\text{PM}_{2.5}$ on the number of veterinary visits across all causes. In all cases our estimates reflect the effect of a change in weekly average $\text{PM}_{2.5}$ for the preceding seven day period. We estimate the relationship separately for dogs and cats using a binscatter regression model (Cattaneo et al., 2024). This model flexibly estimates the relationship between the number of vet visits and $\text{PM}_{2.5}$, while controlling for the variables and fixed effects specified in Equation (1). Each circle marker corresponds to a point estimate and the whiskers display the 95% confidence intervals, based on standard errors clustered by NUTS3 region.

For both species, the effect of $\text{PM}_{2.5}$ on number of visits is linearly increasing and statistically significant. A one microgram per cubic meter increase in $\text{PM}_{2.5}$ leads to 0.1 additional

visits/day for dogs and 0.04 additional visits/day for cats. 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 $PM_{2.5}$

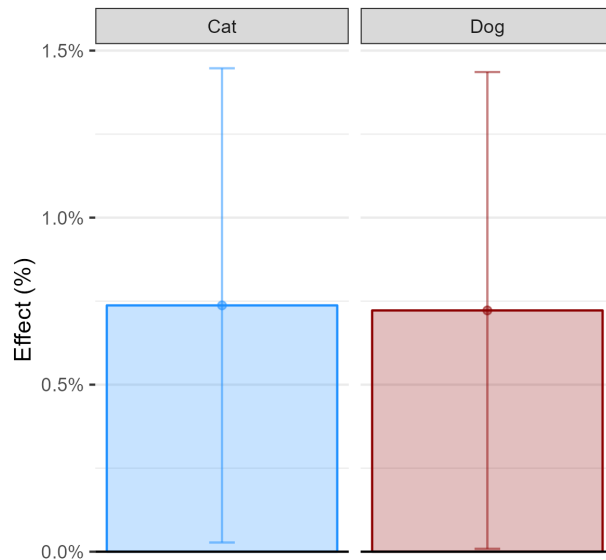


Notes: This figure plots results from Poisson regressions of the count of daily vet visits for all causes on $PM_{2.5}$ concentration levels. The measure of air pollution used is daily values for the rolling weekly average up to that day. We utilize the binscatter method (Cattaneo et al. (2024)). All regressions include controls for pet age, sex, and weather, as well as NUTS3 and day-of-sample fixed effects.

Figure 2 reports the percentage effects implied by our Poisson regression estimates of the relationship between $PM_{2.5}$ and daily number of visits. We find that a one microgram per cubic meter increase in $PM_{2.5}$ leads to a 0.7% increase in daily visits for both cats and dogs.

The 95% confidence interval for dogs spans 0.012% to 1.461% and for cats spans 0.022% to 1.458%.

Figure 2: Estimated Effect of Ambient $PM_{2.5}$ on Total Number of Vet Visits



Notes: This figure presents the estimates from Poisson regressions of the daily count of vet visits across all causes on 7-day rolling averages of $PM_{2.5}$ concentration levels. 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 dogs and cats.

Our estimated effect sizes are of a similar order of magnitude to those found in human health studies on air pollution and hospitalizations. Systematic reviews by [Atkinson et al. \(2014\)](#) and [Requia et al. \(2018\)](#) both find that a $10 \mu\text{g}/\text{m}^3$ in daily $PM_{2.5}$ leads to a roughly 1% increase in all-cause hospital admissions.⁶ [Deryugina et al. \(2019\)](#) estimates that a $10 \mu\text{g}/\text{m}^3$ increase in daily $PM_{2.5}$ leads to a 2.2% increase in one-day all-cause hospitalizations amongst US Medicare recipients. If we convert our estimates into comparable units, they indicate an equivalent $10 \mu\text{g}/\text{m}^3$ increase in daily $PM_{2.5}$ leads to a roughly 1% increase in

⁶The [Atkinson et al. \(2014\)](#) study continues to underpin the UK government's assumptions on the health impacts of air pollution for use in cost-benefit analysis.

all-cause veterinary admissions.⁷

4.2 Vet Visits by Main Presenting Complaint

Figure 3 examines how air quality affects the count of visits depending on the main presenting complaint. As in Figure 2, we report effects in proportionate terms since our estimates come from Poisson regressions. Here, we see that the increase in overall vet visits is primarily driven by the “Other Unwell” category: a one microgram per cubic meter increase in $PM_{2.5}$ leads to a 1.3% increase in daily visits classified as “Other Unwell” for cats, and a 1.2% increase for dogs.

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” seems to encompass visits that are not easily categorised 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. There is no main presenting complaint category for cardiovascular or neurological problems, so it makes sense that pets with symptoms originating from these sources may be classified in the “Other Unwell” category.

There is a specific main presenting complaint category for “Respiratory” visits, and here we find no significant effect. 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

⁷Here, we simply divide our estimate by seven to convert from weekly rolling average pollution to a one day estimate. When running our regressions using contemporaneous daily pollution instead of weekly rolling average pollution, we find a similar effect size of 1–2%, although the estimate is not statistically significant.

brought in to the vet.

Lastly, it is reassuring that we do not find 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 find a significant increase in vet visits for “Vaccination” or “Post-Op” on more polluted days. Therefore, specifications based on these other categories serve as placebo tests that further support the robustness of the observed effects on visits classified as “Other Unwell”.

4.3 Vet Visits by Pet Age

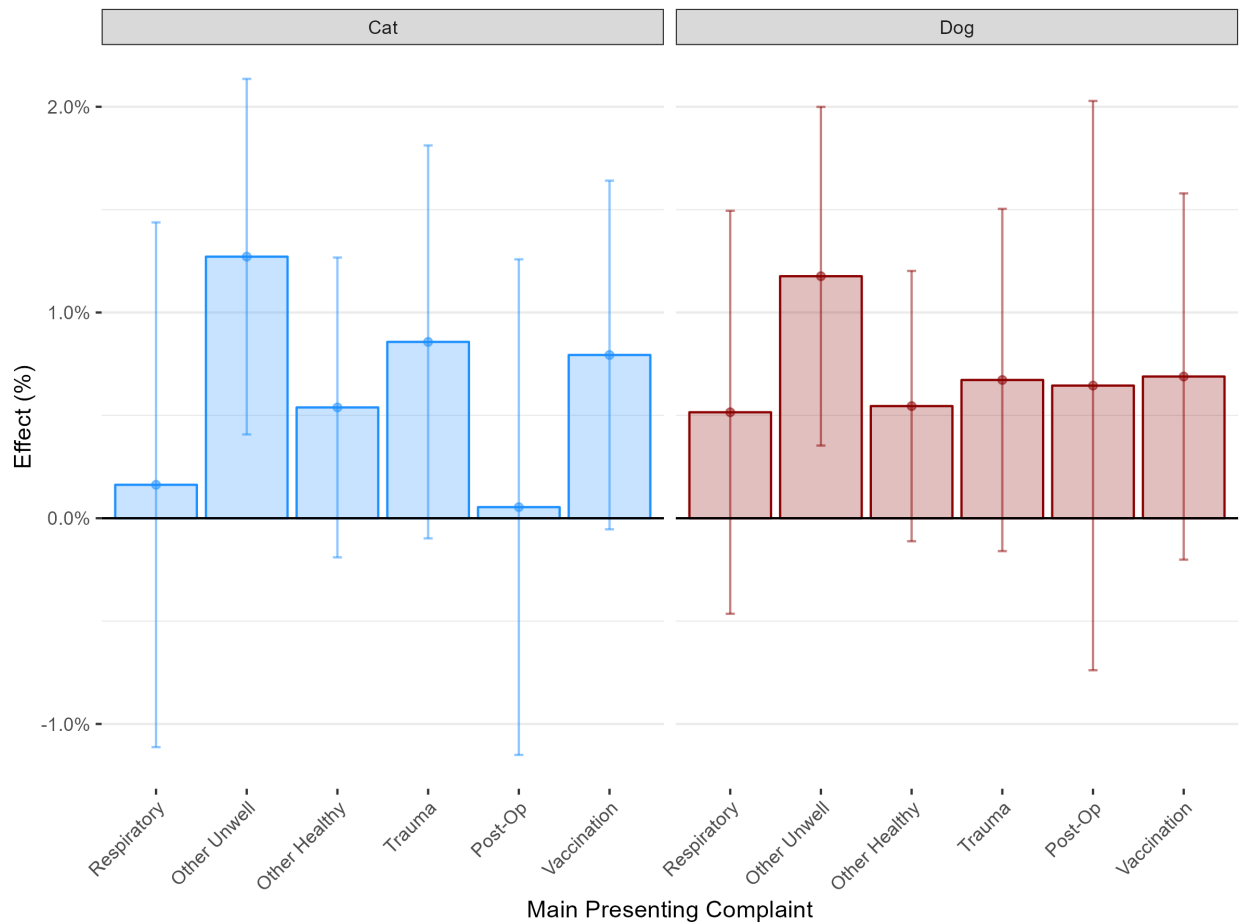
Much of the literature on how air pollution affects human health highlights that vulnerability varies across individuals, with age being a key risk factor. We therefore explore heterogeneity in our effects by age group. Figure 4 provides age-group-specific estimates of the effect of $PM_{2.5}$ on all-cause visits in proportionate terms. Though we observe a slight increase in effect size with age, the differences across age groups are not statistically significant.

5 Conclusion

Using detailed data on veterinarian visits spanning the United Kingdom, we uncover the extent to which air pollution impacts petcare utilization. We find that increases in $PM_{2.5}$ concentration levels lead to significant increases in vet visits for pet cats and dogs.

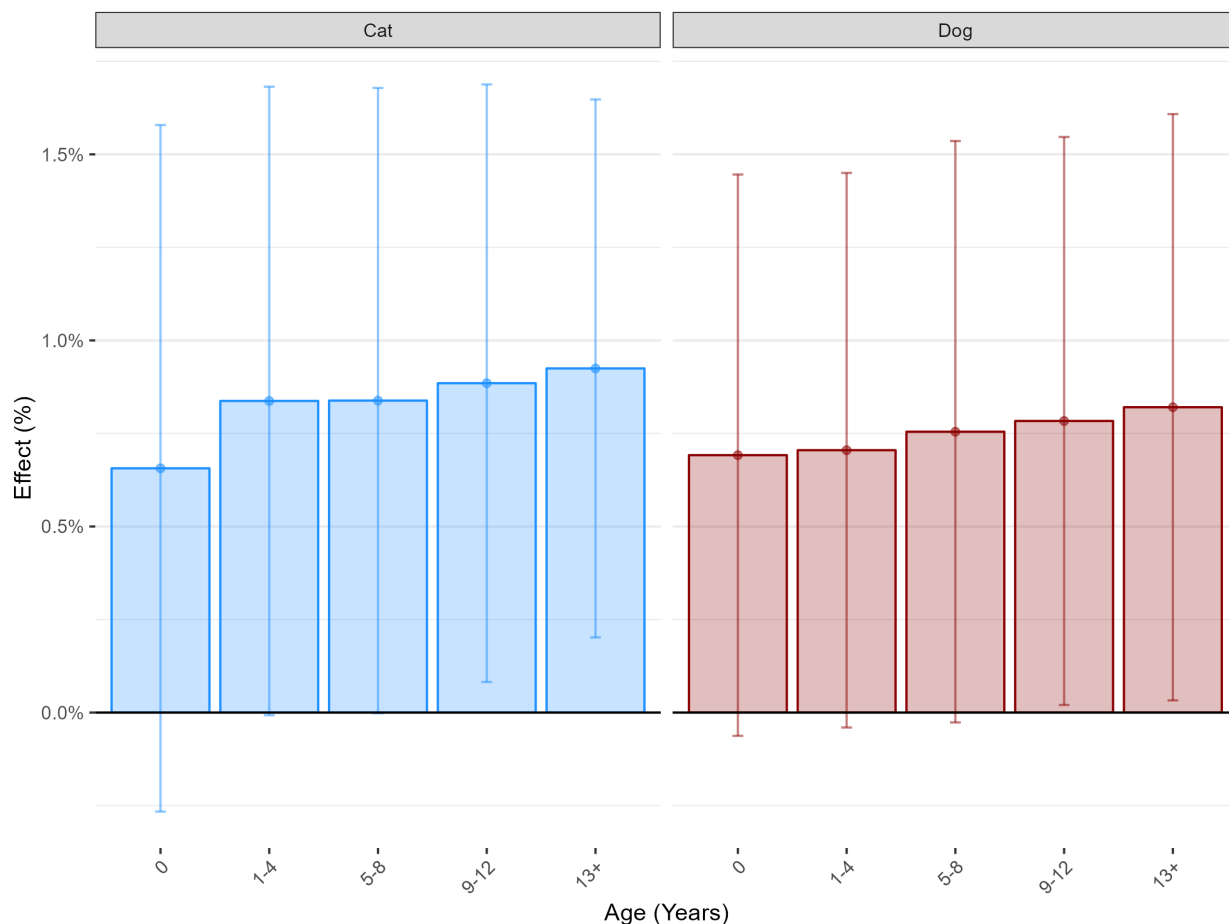
In aggregate, our estimates suggest that reducing ambient $PM_{2.5}$ levels to a maximum of

Figure 3: 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 control for pet age, sex, and 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.

Figure 4: Estimated Effect of Ambient $PM_{2.5}$ on Number of All-Cause Vet Visits by Age Group



Notes: This figure presents estimates and 95% confidence intervals from Poisson regressions of the count of all-cause vet visits on $PM_{2.5}$ concentration levels interacted with indicators for age categories. The measure of air pollution used is daily values for the rolling weekly average up to that day. We estimate separate Poisson regressions for cats and dogs. All regressions include controls for pet age, sex and various weather controls, as well as NUTS3 and day-of-sample fixed effects.

5 $\mu\text{g}/\text{m}^3$ as recommended by the World Health Organization (WHO) would lead to eighty thousand fewer vet visits each year (a 0.4% reduction).⁸ The resulting annual savings in petcare utilization costs alone are roughly fifteen million pounds, and the total economic costs are likely to be considerably higher.⁹

In future work, we plan to link increases in petcare utilization to subsequent changes in pet health. This will allow us to quantify owners' willingness to pay to improve their pets' health. The pet-care market has grown by over 66% in the last decade, significantly outpacing growth in the wider economy ([The Economist, 2019](#)). Despite this, there remains relatively little empirical evidence on the willingness-to-pay to improve pet health, especially in ways that can inform cost-benefit analysis for policies that yield improvements in animal well-being ([Sunstein, 2024](#)). Our findings raise the possibility that a growing share of the benefits from air pollution regulations may come from the avoided petcare costs associated with reduced exposure to poor air quality.

⁸There are approximately 5,000 vet practices in the UK ([Competition and Markets Authority, 2024](#)). Our SAVSNET data include 500 sites corresponding to 250 practices, noting that some practices have multiple sites. There are 0.0173 all-cause vet visits per year per capita to practices in the SAVSNET data. This implies 0.346 all-cause vet visits per year per capita for the entire UK. The population-weighted average level of $\text{PM}_{2.5}$ in 2022 was 8.1 $\mu\text{g}/\text{m}^3$. Multiplying this by the UK population and the assumed vet visits per capita yields that there were 178,000 more vet visits in 2022 due to air pollution. This constitutes 0.8% of all vet visits in the UK. 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 3.75 $\mu\text{g}/\text{m}^3$ in 2022. This would imply an associated reduction in vet visits of around 82,000 in 2022. This reduction constitutes 0.4% of all UK vet visits.

⁹The UK spends roughly ten billion pounds on pets ([Office for National Statistics, 2024](#)), and roughly 40% of pet spending is on vet care, insurance, pharmaceuticals and diagnostics ([Bloomberg Intelligence, 2023](#)). Assuming that pollution-related vet visits have the same cost as the average visit, 0.4% of four billion pounds is roughly fifteen million pounds.

References

- Atkinson, R W, S Kang, H R Anderson, I C Mills, and H A Walton. 2014. “Epidemiological time series studies of PM2.5 and daily mortality and hospital admissions: a systematic review and meta-analysis.” *Thorax*, 69(7): 660–665.
- Bloomberg Intelligence. 2023. “Global Pet Industry To Grow To \$500 Billion By 2030.”
- Budolfson, Mark, Romain Espinosa, Bob Fischer, and Nicolas Treich. 2024. “Monetizing Animal Welfare Impacts for Benefit–Cost Analysis.” *Journal of Benefit-Cost Analysis*, 1–18.
- Calderón-Garcidueñas, Lilian, Luis O González-González, Randy J Kulesza, Tatiana M Fech, Gabriela Pérez-Guillé, Miguel Angel Jiménez-Bravo Luna, Rosa Eugenia Soriano-Rosales, Edelmira Solorio, Jose de Jesus Miramontes-Higuera, Aline Gómez-Maqueo Chew, et al. 2017. “Exposures to fine particulate matter (PM2.5) and ozone above USA standards are associated with auditory brainstem dysmorphology and abnormal auditory brainstem evoked potentials in healthy young dogs.” *Environmental research*, 158: 324–332.
- Carlson, Deven, Simon Haeder, Hank Jenkins-Smith, Joseph Ripberger, Carol Silva, and David Weimer. 2020. “Monetizing Bowser: A Contingent Valuation of the Statistical Value of Dog Life–Corrigendum.” *Journal of Benefit-Cost Analysis*, 11(1): 150–150.
- Cattaneo, Matias D, Richard K Crump, Max H Farrell, and Yingjie Feng. 2024. “On binscatter.” *American Economic Review*, 114(5): 1488–1514.
- Chen, Shuai, Paulina Oliva, and Peng Zhang. 2022. “The effect of air pollution on migration: Evidence from China.” *Journal of Development Economics*, 156: 102833.
- Competition and Markets Authority. 2024. “Consultation on the proposal to make a market investigation reference into veterinary services for household pets in the UK.”
- Costello, Christopher, Lynne Lewis, John Lynham, and Leslie Richardson. 2023. “The charisma premium: Iconic individuals and wildlife values.” *Journal of Environmental Economics and Management*, 122: 102872.
- Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif. 2019. “The mortality and medical costs of air pollution: Evidence from changes in wind direction.” *American Economic Review*, 109(12): 4178–4219.
- Ferris, Ann E., and Eyal G. Frank. 2021. “Labor market impacts of land protection: The Northern Spotted Owl.” *Journal of Environmental Economics and Management*, 109: 102480.
- Frank, Eyal, and Anant Sudarshan. 2023. “The Social Costs of Keystone Species Collapse: Evidence from the Decline of Vultures in India.” *Becker Friedman Institute for Economics Working Paper*, , (2022-165).

- Fuller, Richard, Philip J Landrigan, Kalpana Balakrishnan, Glynda Bathan, Stephan Bose-O'Reilly, Michael Brauer, Jack Caravanos, Tom Chiles, Aaron Cohen, Lilian Corra, Maureen Cropper, Greg Ferraro, Jill Hanna, David Hanrahan, Howard Hu, David Hunter, Gloria Janata, Rachael Kupka, Bruce Lanphear, Maureen Lichtveld, Keith Martin, Adetoun Mustapha, Ernesto Sanchez-Triana, Karti Sandilya, Laura Schaeffli, Joseph Shaw, Jessica Seddon, William Suk, Martha María Téllez-Rojo, and Chonghuai Yan. 2022. "Pollution and health: a progress update." *The Lancet Planetary Health*, 6(6): e535–e547.
- Giugliano, Roberta, Maria Ines Crescio, Valeria Cosma, Valentina Ciccotelli, Barbara Vivaldi, and Elisabetta Razzuoli. 2024. "Mortality and heavy metals environmental exposure: a study in dogs." *Frontiers in Veterinary Science*, 10.
- Liang, Yuanning, Ivan Rudik, Eric Yongchen Zou, Alison Johnston, Amanda D Rodewald, and Catherine L Kling. 2020. "Conservation cobenefits from air pollution regulation: Evidence from birds." *Proceedings of the National Academy of Sciences*, 117(49): 30900–30906.
- Lin, Chung-Hui, Pei-Ying Lo, Huey-Dong Wu, Chinhao Chang, and Lih-Chiann Wang. 2018. "Association between indoor air pollution and respiratory disease in companion dogs and cats." *Journal of veterinary internal medicine*, 32(3): 1259–1267.
- Losacco, Caterina, and Antonella Perillo. 2017. "Particulate matter air pollution and respiratory impact on humans and animals." *Environmental Science and Pollution Research*, 25(34): 083002.
- Muller, Nicholas Z. 2014. "Boosting GDP growth by accounting for the environment." *Science*, 345(6199): 873–874.
- Muller, Nicholas Z, Robert Mendelsohn, and William Nordhaus. 2011. "Environmental accounting for pollution in the United States economy." *American Economic Review*, 101(5): 1649–1675.
- NRC and NAS. 2010. "Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use." National Research Council (US). Committee on Health, Environmental, and Other External Costs and Benefits of Energy Production and Consumption. National Academies Press.
- Office for National Statistics. 2024. "Household expenditures on pets and related products."
- Requia, Weeberb J, Matthew D Adams, Altaf Arain, Stefania Papatheodorou, Petros Koutrakis, and Moataz Mahmoud. 2018. "Global Association of Air Pollution and Cardiorespiratory Diseases: A Systematic Review, Meta-Analysis, and Investigation of Modifier Variables." *American Journal of Public Health*, 108(S2): S123–S130.

- Richardson, Leslie, and Lynne Lewis.** 2022. “Getting to know you: individual animals, wildlife webcams, and willingness to pay for brown bear preservation.” *American Journal of Agricultural Economics*, 104(2): 673–692.
- Sager, Lutz.** 2019. “Estimating the effect of air pollution on road safety using atmospheric temperature inversions.” *Journal of Environmental Economics and Management*, 98: 102250.
- Sunstein, Cass R.** 2024. “Regulators Should Value Nonhuman Animals.” *SSRN Working Paper*.
- Sánchez-Vizcaíno, Fernando, Philip H. Jones, Tarek Menacere, Bethaney Heayns, Maya Wardeh, Jenny Newman, Alan D. Radford, Susan Dawson, Rosalind Gaskell, Peter J. M. Noble, Sally Everitt, Michael J. Day, and Katie McConnell.** 2015. “Small animal disease surveillance.” *Veterinary Record*, 177(23): 591–594.
- The Economist.** 2019. “Which country spends the most on its pets?” <https://www.economist.com/graphic-detail/2020/02/11/which-country-spends-the-most-on-its-pets>.
- Viscusi, W. Kip, and Clayton J. Masterman.** 2017. “Income Elasticities and Global Values of a Statistical Life.” *Journal of Benefit-Cost Analysis*, 8(2): 226–250.

Online Appendix (Not For Publication)

The Impacts of Pollution on Petcare Utilization and Spending

*Olivier Deschenes, Stephen Jarvis, and Akshaya Jha**

A Further Detail on the Data Used

Figure [A.1](#) shows a map of the UK. Each of the NUTS3 regions is shaded in blue based on the average number of daily vet visits we observe in our sample. We have data from a selection of vet 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 practices that the team at the University of Liverpool have managed to recruit into providing data to the SAVSNET program. For example, there is a relatively high degree of participation by veterinary practices in Devon in the south west, but relatively limited participation by veterinary practices in London or Northern Ireland.

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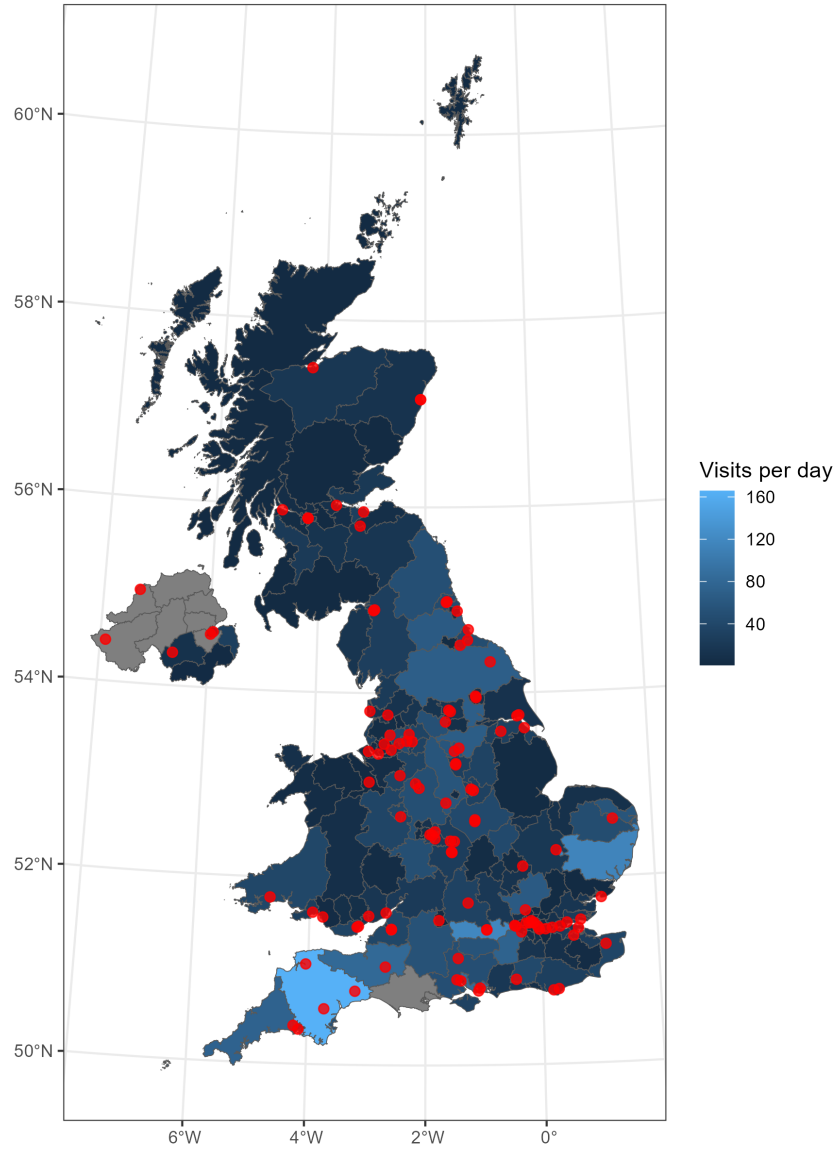
The red dots on the map represent the air pollution monitors that our air quality data is taken from. These comprise the core set of pollution monitors maintained by the UK government. The monitors collect pollution readings every hour on a wide range of pollutants. Monitors are spread across the country and tend to be sited near urban centers where people live.

Importantly, not all NUTS3 regions have a pollution monitor, and many have multiple monitors. We therefore calculate the daily pollution value for a given NUTS3 region by taking the inverse distance weighted average of the three nearest pollution monitors, as measured by their distance to the centroid of the NUTS3 region. Before averaging, we exclude any monitors in a given day with missing values and monitors more than 50km from the centroid of the NUTS3 region in question.

Figure [A.2](#) 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.

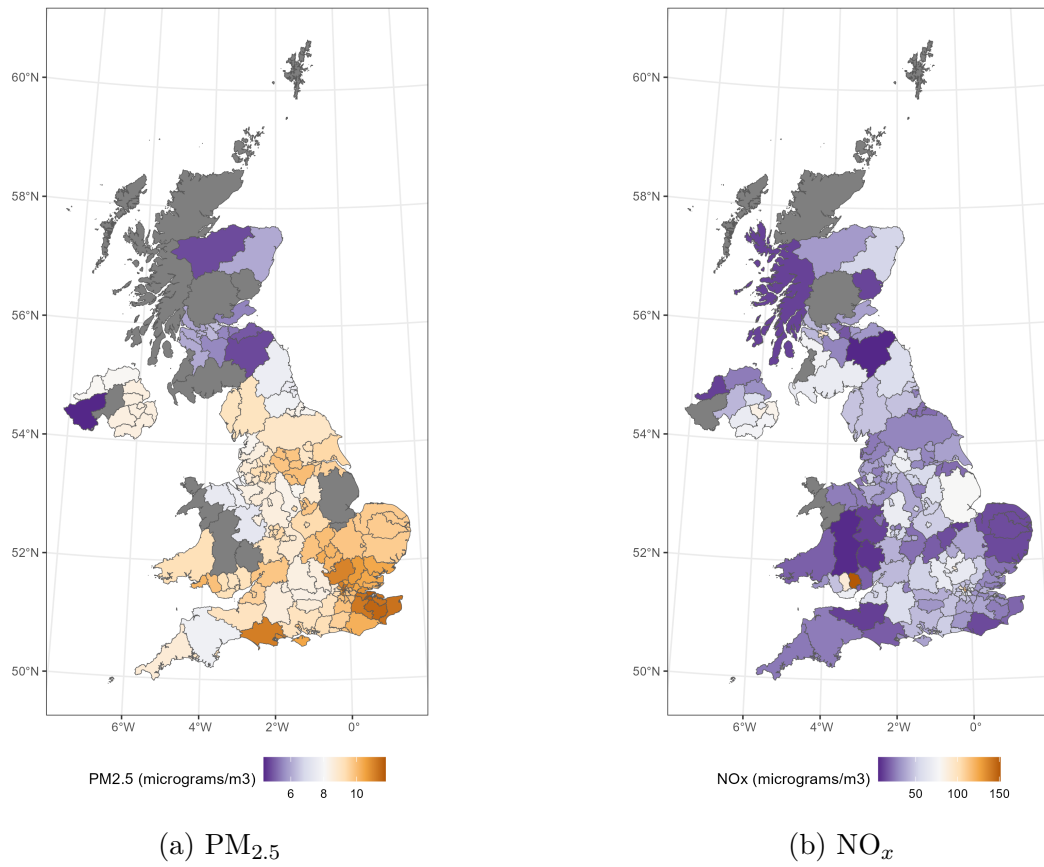
Figure [A.3](#) shows the average values for key weather variables for the various NUTS3 regions in the UK. These weather variables are primarily used as controls in our analysis. Temperatures are higher in the south of the country, while precipitation is concentrated in the north and west. The prevailing winds in the UK blow from west to east bringing

Figure A.1: Map of Pollution and Weather Monitoring Stations



Notes: This figure plots the location of the different pollution monitoring sites used in our analysis. The regions plotted are the NUTS3 regions included in our pet visit data. Each region is shaded according to the average daily number of vet visits over the sample period January 2017 to September 2022.

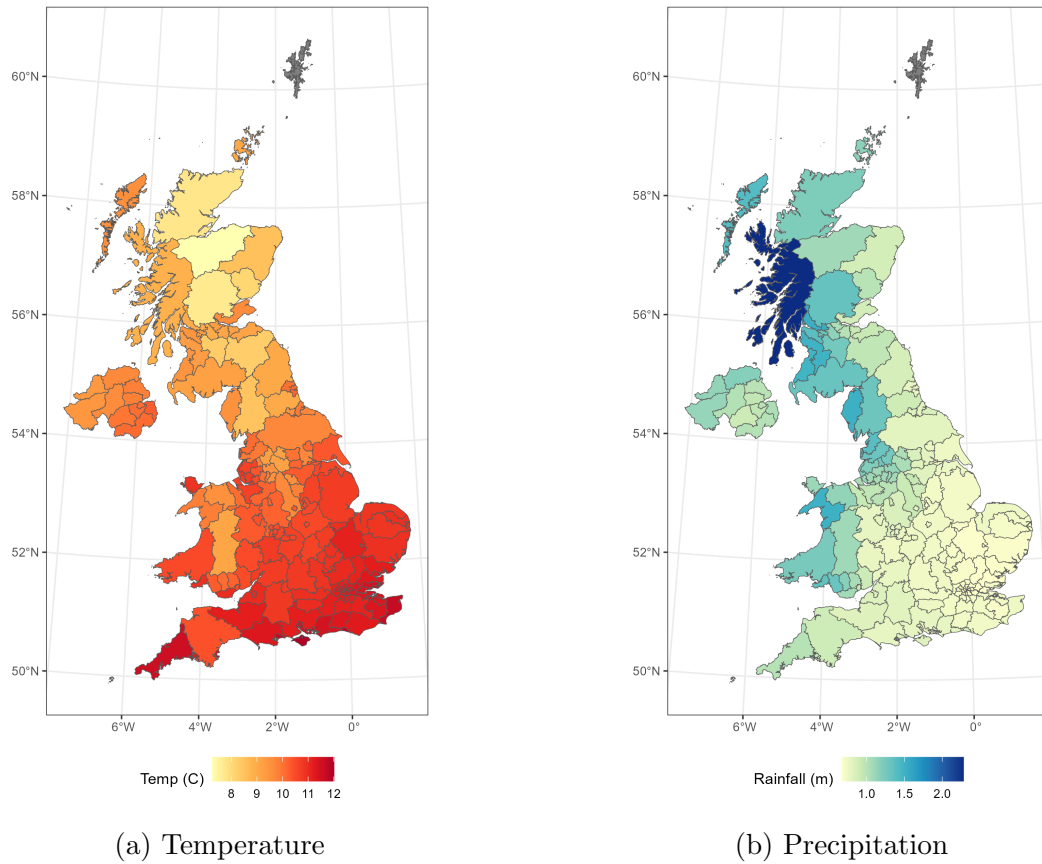
Figure A.2: Maps of Average Pollution



Notes: This figure plots average levels of pollution over the sample period January 2017 to September 2022 for each NUTS3 region.

moisture in off the Atlantic. This also has important implications for pollution exposure, with pollution being blown from western to eastern regions. Even within cities, there tends to be higher levels of pollution in the eastern portion due to these prevailing winds. Some of the highest pollution days in the UK occur when the wind direction is reversed and blowing from the south and east. During these periods, pollution is blown to the UK from Continental Europe, with the southeast regions of the UK again being the most acutely affected.

Figure A.3: Map of Average Weather



Notes: This figure plots average weather over the sample period January 2017 to September 2022 for each NUTS3 region.

B Further Results

B.1 All-Cause Vet Visits

Table B.1 provides the regression coefficients from the relationship plotted in Figure 2. Expressed in proportional terms, we can see that a one microgram per cubic meter increase in $PM_{2.5}$ leads to a 0.7% increase in daily number of visits for both cats and dogs.

Table B.1: Effects of $PM_{2.5}$ on Daily Total Number of Visits

Model:	Cat (1)	Dog (2)
<i>Variables</i>		
PM _{2.5}	0.0074** (0.0036)	0.0072** (0.0036)
Species	Cat	Dog
Age Controls	Yes	Yes
Sex Controls	Yes	Yes
Weather Controls	Yes	Yes
<i>Fixed-effects</i>		
NUTS3 Area	Yes	Yes
Date	Yes	Yes
<i>Fit statistics</i>		
Observations	316,175	316,319
Squared Correlation	0.81927	0.83849
Pseudo R ²	1.3390	1.1102
BIC	5.87×10^{11}	9.75×10^{11}
<i>Clustered (NUTS3 Area) standard-errors in parentheses</i>		
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>		

Notes: This table presents results from Poisson regressions of the count of all vet visits on $PM_{2.5}$ concentration levels. 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 various weather controls as well as NUTS3 and day-of-sample fixed effects.

B.2 Vet Visits by Main Presenting Complaint

Table B.2 provides the regression coefficients from the relationship plotted in Figure 3. Expressed in proportional terms, a one microgram per cubic meter increase in $PM_{2.5}$ leads

to a 1.2-1.3% increase in daily visits classed as “Other Unwell” for both cats and dogs.

Table B.2: Effects of $PM_{2.5}$ on Total Number of Visits by Reason

Model:	Respiratory (1)	Other Unwell (2)	Other Healthy (3)	Trauma (4)	Post-Op (5)	Vaccination (6)
<i>Variables</i>						
PM2.5	0.0052 (0.0050)	0.0118*** (0.0042)	0.0055 (0.0034)	0.0067 (0.0042)	0.0064 (0.0071)	0.0069 (0.0045)
Species	Dog	Dog	Dog	Dog	Dog	Dog
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	295,673	316,024	316,166	315,276	314,657	314,963
Squared Correlation	0.21596	0.68500	0.70015	0.54183	0.60361	0.76647
Pseudo R ²	0.19420	3.2265	1.6894	0.09592	-0.24061	1.5418
BIC	9.04×10^{10}	4.74×10^{11}	5.63×10^{11}	2.24×10^{11}	2.94×10^{11}	5.38×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses

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

(a) Dogs

Model:	Respiratory (1)	Other Unwell (2)	Other Healthy (3)	Trauma (4)	Post-Op (5)	Vaccination (6)
<i>Variables</i>						
PM2.5	0.0016 (0.0065)	0.0127*** (0.0044)	0.0054 (0.0037)	0.0086* (0.0049)	0.0005 (0.0061)	0.0079* (0.0043)
Species	Cat	Cat	Cat	Cat	Cat	Cat
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	269,768	313,828	313,673	302,356	301,407	313,886
Squared Correlation	0.14804	0.62174	0.64079	0.39692	0.42059	0.71544
Pseudo R ²	0.18264	-0.25124	-0.98902	0.22565	0.19238	-6.6687
BIC	5.64×10^{10}	2.91×10^{11}	3.39×10^{11}	1.33×10^{11}	1.61×10^{11}	3.67×10^{11}

Clustered (NUTS3 Area) standard-errors in parentheses

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

(b) Cats

Notes: This table presents the results from Poisson regressions of the count of vet visits for various reasons on $PM_{2.5}$ concentration levels. 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 various weather controls, as well as NUTS3 and day-of-sample fixed effects. Models vary based on their dependent variable.

B.3 Vet Visits by Pet Age

Table B.3 provides the regression coefficients from the relationship plotted in Figure 4. The average all-cause effect was 0.7% for both cats and dogs, and as noted in the main text, there is some evidence of larger effects in older age categories.

Table B.3: Effects of $PM_{2.5}$ on Total Number of Visits by Age Group

Model:	0 (1)	1-4 (2)	5-8 (3)	9-12 (4)	13+ (5)
<i>Variables</i>					
PM2.5	0.0069* (0.0038)	0.0070* (0.0038)	0.0075* (0.0040)	0.0078** (0.0039)	0.0082** (0.0040)
Species	Dog	Dog	Dog	Dog	Dog
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	315,869	316,168	316,168	316,175	316,025
Squared Correlation	0.73290	0.80777	0.80441	0.79832	0.61953
Pseudo R ²	-23.333	1.5139	1.6368	1.9384	-0.01938
BIC	3.42×10^{11}	4.74×10^{11}	4.46×10^{11}	4.12×10^{11}	2.45×10^{11}
<i>Clustered (NUTS3 Area) standard-errors in parentheses</i>					
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>					

(a) Dogs

Model:	0 (1)	1-4 (2)	5-8 (3)	9-12 (4)	13+ (5)
<i>Variables</i>					
PM2.5	0.0066 (0.0047)	0.0084* (0.0043)	0.0084* (0.0043)	0.0088** (0.0041)	0.0092** (0.0037)
Species	Cat	Cat	Cat	Cat	Cat
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	307,810	316,025	311,116	313,465	313,217
Squared Correlation	0.58519	0.71490	0.71112	0.70984	0.73604
Pseudo R ²	0.16389	-0.26732	-0.11568	-0.05613	-0.13995
BIC	2.07×10^{11}	2.64×10^{11}	2.49×10^{11}	2.43×10^{11}	2.48×10^{11}
<i>Clustered (NUTS3 Area) standard-errors in parentheses</i>					
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>					

(b) Cats

Notes: This table presents results from Poisson regressions of the count of all-cause vet visits on $PM_{2.5}$ concentration levels interacted with indicators of pet age categories. 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 various weather controls, as well as NUTS3 and day-of-sample fixed effects.

C Results from Instrumental Variables Specifications

To further address concerns about unobserved local factors correlated with $PM_{2.5}$ and vet visits, we consider an instrumental variables approach. 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 5,341.^b 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.^c

One challenge of implementing an instrumental variables approach in our setting is doing so using our Poisson specification and rich set of fixed effects. Here, 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.

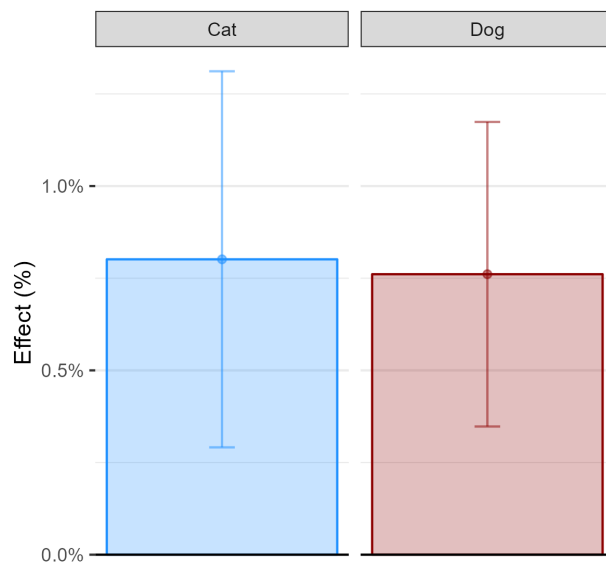
Figure C.1 and Table C.1 show the results for all-cause visits estimated using instrumental variables. The coefficient estimates for both cats and dogs are very similar in magnitude to those found in the main text using a fixed effects approach.

Figure C.2 and Table C.2 present 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 also see small, statistically significant effects in the “Other Healthy”

^bEach instrument separately also has a strong first stage with an F-statistic of the same order of magnitude. The wind direction instrument has a stronger first stage than the thermal inversions instrument.

^cFor the binary thermal inversions instrument, the first stage Wald F-statistic is 11.2.

Figure C.1: Instrumental Variables Estimated Effect of Ambient $PM_{2.5}$ on Total Number of Vet Visits



Notes: This figure presents the estimates and 95% confidence intervals from instrumental variables Poisson regressions of the daily count of vet visits across all causes on 7-day rolling averages of $PM_{2.5}$ concentration levels. We construct instruments for $PM_{2.5}$ based on both wind direction and thermal inversions; see Appendix Section C for more details. 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 IV Poisson regressions for dogs and cats.

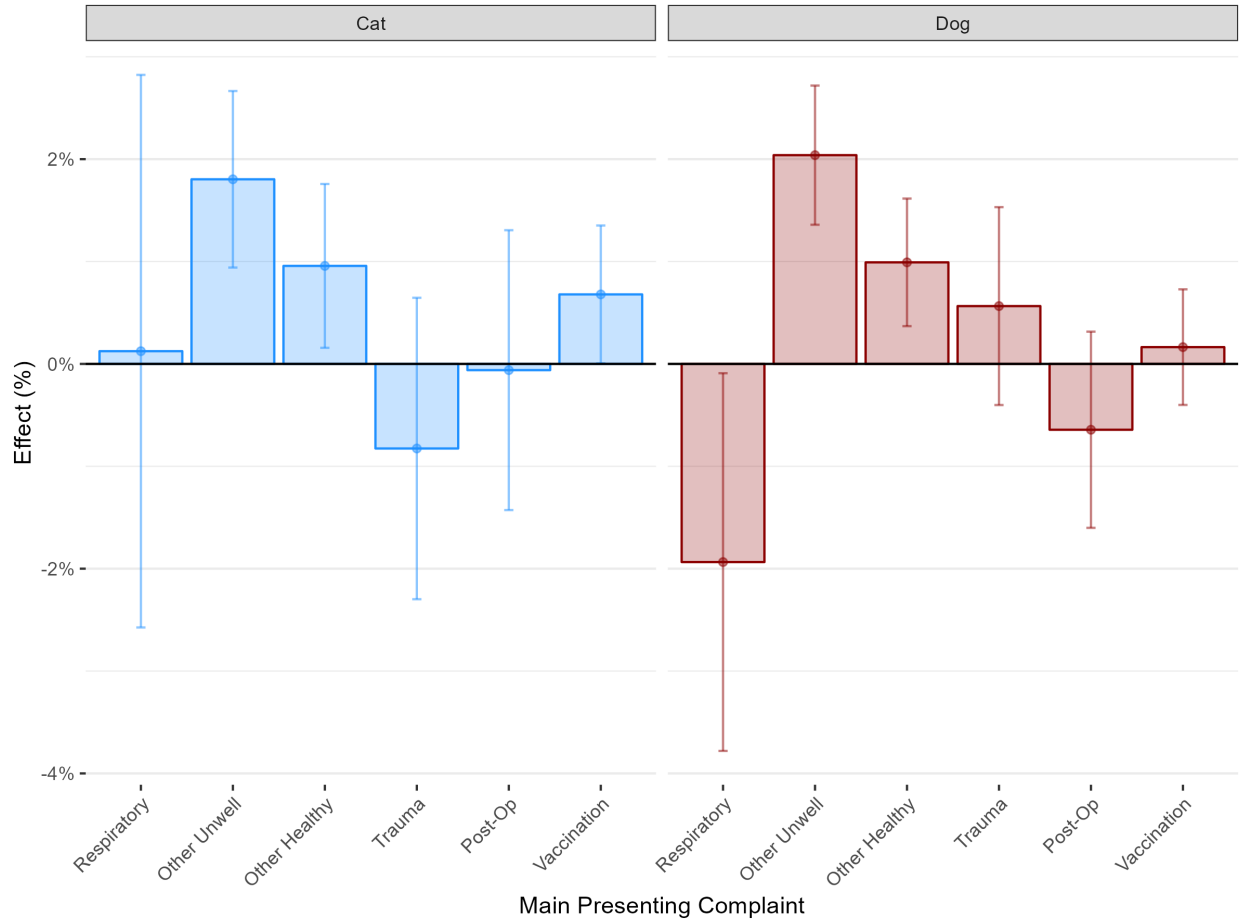
Table C.1: Instrumental Variables Estimated Effect of Ambient $PM_{2.5}$ on Total Number of Vet Visits

Model:	Cat (1)	Dog (2)
<i>Variables</i>		
PM2.5	0.0080*** (0.0026)	0.0076*** (0.0021)
Species	Cat	Dog
Age Controls	Yes	Yes
Sex Controls	Yes	Yes
Weather Controls	Yes	Yes
<i>Fixed-effects</i>		
NUTS3 Area	Yes	Yes
Date	Yes	Yes
<i>Fit statistics</i>		
Observations	316,175	316,319
Squared Correlation	0.81927	0.83849
Pseudo R ²	1.3390	1.1102
BIC	5.87×10^{11}	9.75×10^{11}
<i>Custom standard-errors in parentheses</i>		
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>		

Notes: This table presents the results from instrumental variables Poisson regressions of the daily count of vet visits across all causes on 7-day rolling averages of $PM_{2.5}$ concentration levels. We construct instruments for $PM_{2.5}$ based on both wind direction and thermal inversions; see Appendix Section C for more details. 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 IV Poisson regressions for dogs and cats.

category across both cats and 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 for any of the categories of main presenting complaint.

Figure C.2: Instrumental Variables Estimated Effect of Ambient $PM_{2.5}$ on Number of 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 inversions; see Appendix Section C for more details. 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.

Figure C.3 and Table C.3 present the results for all-cause visits by age group estimated using instrumental variables. The effect sizes remain broadly comparable to those in the

Table C.2: Instrumental Variables Estimated Effect of Ambient PM_{2.5} on Number of Vet Visits by Main Presenting Complaint

Model:	Respiratory (1)	Other Unwell (2)	Other Healthy (3)	Trauma (4)	Post-Op (5)	Vaccination (6)
<i>Variables</i>						
PM2.5	-0.0194** (0.0094)	0.0204*** (0.0035)	0.0099*** (0.0032)	0.0056 (0.0049)	-0.0064 (0.0049)	0.0016 (0.0029)
Species	Dog	Dog	Dog	Dog	Dog	Dog
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	295,673	316,024	316,166	315,276	314,657	314,963
Squared Correlation	0.21595	0.68502	0.70014	0.54183	0.60359	0.76646
Pseudo R ²	0.19421	3.2265	1.6894	0.09592	-0.24060	1.5418
BIC	9.04×10^{10}	4.74×10^{11}	5.63×10^{11}	2.24×10^{11}	2.94×10^{11}	5.38×10^{11}
<i>Custom standard-errors in parentheses</i>						
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>						

(a) Dogs

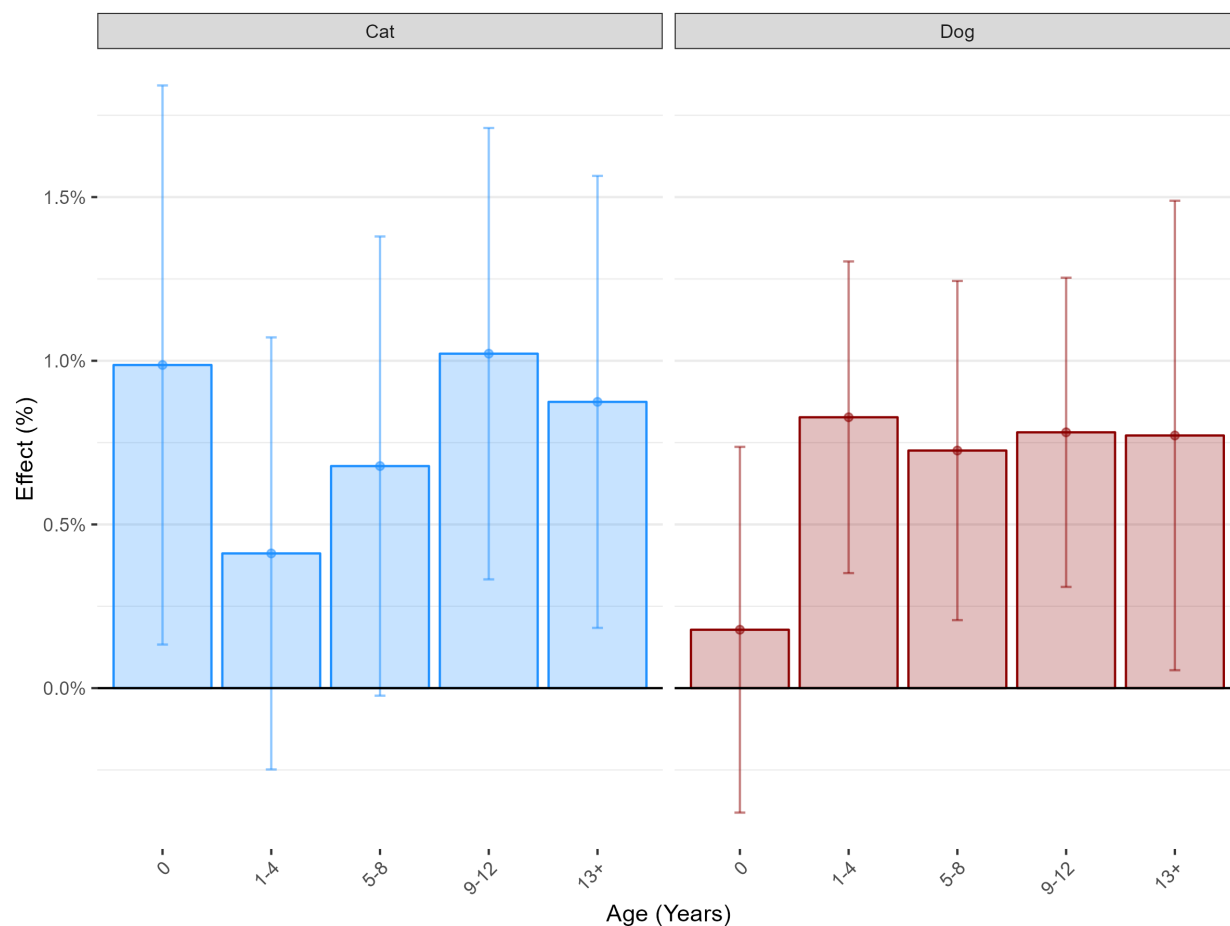
Model:	Respiratory (1)	Other Unwell (2)	Other Healthy (3)	Trauma (4)	Post-Op (5)	Vaccination (6)
<i>Variables</i>						
PM2.5	0.0012 (0.0138)	0.0180*** (0.0044)	0.0096** (0.0041)	-0.0083 (0.0075)	-0.0006 (0.0070)	0.0068** (0.0034)
Species	Cat	Cat	Cat	Cat	Cat	Cat
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>						
NUTS3 Area	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
Observations	269,768	313,828	313,673	302,356	301,407	313,886
Squared Correlation	0.14804	0.62176	0.64079	0.39691	0.42058	0.71544
Pseudo R ²	0.18264	-0.25124	-0.98902	0.22566	0.19238	-6.6687
BIC	5.64×10^{10}	2.91×10^{11}	3.39×10^{11}	1.33×10^{11}	1.61×10^{11}	3.67×10^{11}
<i>Custom standard-errors in parentheses</i>						
<i>Signif. Codes: ***: 0.01, **: 0.05, *: 0.1</i>						

(b) Cats

Notes: This table presents results 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 inversions; see Appendix Section C for more details. 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.

main specification, although they are noisier with less of a clear stable pattern across age groups.

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



Notes: This figure presents estimates and 95% confidence intervals from instrumental variables Poisson regressions of the count of all-cause vet visits on $PM_{2.5}$ concentration levels interacted with indicators for age categories. 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 inversions; see Appendix Section C for more details. All regressions include controls for pet age, sex and various weather controls, as well as NUTS3 and day-of-sample fixed effects.

Table C.3: Instrumental Variables Estimated Effect of Ambient PM_{2.5} on Number of All-Cause Vet Visits by Age Group

Model:	0 (1)	1-4 (2)	5-8 (3)	9-12 (4)	13+ (5)
<i>Variables</i>					
PM2.5	0.0018 (0.0028)	0.0083*** (0.0024)	0.0073*** (0.0026)	0.0078*** (0.0024)	0.0077** (0.0037)
Species	Dog	Dog	Dog	Dog	Dog
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	315,869	316,168	316,168	316,175	316,025
Squared Correlation	0.73289	0.80777	0.80441	0.79832	0.61953
Pseudo R ²	-23.332	1.5139	1.6368	1.9384	-0.01938
BIC	3.42×10^{11}	4.74×10^{11}	4.46×10^{11}	4.12×10^{11}	2.45×10^{11}

Custom standard-errors in parentheses

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

(a) Dogs

Model:	0 (1)	1-4 (2)	5-8 (3)	9-12 (4)	13+ (5)
<i>Variables</i>					
PM2.5	0.0099** (0.0044)	0.0041 (0.0034)	0.0068* (0.0036)	0.0102*** (0.0035)	0.0087** (0.0035)
Species	Cat	Cat	Cat	Cat	Cat
Age Controls	Yes	Yes	Yes	Yes	Yes
Sex Controls	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>					
NUTS3 Area	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	307,810	316,025	311,116	313,465	313,217
Squared Correlation	0.58520	0.71491	0.71112	0.70984	0.73604
Pseudo R ²	0.16389	-0.26732	-0.11568	-0.05613	-0.13995
BIC	2.07×10^{11}	2.64×10^{11}	2.49×10^{11}	2.43×10^{11}	2.48×10^{11}

Custom standard-errors in parentheses

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

(b) Cats

Notes: This table presents results from instrumental variables Poisson regressions of the count of all-cause vet visits on PM_{2.5} concentration levels interacted with indicators for age categories. 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 inversions; see Appendix Section C for more details. All regressions include controls for pet age, sex and various weather controls, as well as NUTS3 and day-of-sample fixed effects.