An assessment of the contribution of livestock intensity on particulate matter concentration in Italy

Jacopo Lunghi*, Maurizio Malpede† and Lara Aleluia Reis‡

Abstract

The linkage between agricultural activities, particularly livestock farming, to atmospheric pollution is broadly acknowledged and its magnitude is widely studied. Lombardy, recognized as one of Europe's critical air pollution zones, has significantly large contributions from this sector. Although studies aimed at informing policy reflect uncertain and moderate pollution reduction even under simulated stringent policy scenarios, granular causal evidence at a sub-sector level remains insufficient to inform local and regional policies effectively. In this study, we employ spatial econometrics to investigate the specific impact of bovine and swine farming on the concentration levels of ammonia (NH3) and coarse particulate matter (PM10) in Lombardy's atmosphere. Our findings indicate that an increase of 1000 units in livestock—equating to roughly a 1% and 0.3% rise in the average per-quadrant bovine and swine populations respectively—triggers a corresponding daily increase in NH3 and PM10 concentrations. These increases are quantified as 0.26 [0.22; 0.33] and 0.29 [0.27; 0.41] $\mu g/m^3$ for bovines (about 2% and 1% of the respective daily averages) and 0.01 [0.01; 0.05] and 0.04 [0.004; 0.16] $\mu g/m^3$ for swine. Notably, these impacts are intensified under northerly upwind conditions, minimizing the potential for concurrent pollution sources and reinforcing the robustness of our estimated impacts. Finally, using these findings, we extrapolate the potential environmental implications of reducing livestock emissions. Our analysis suggests that this sub-sector could account for over 20% of total pollution exposure, empathizing the need for targeted mitigation strategies for the sector.

Keywords: Ammonia; Particulate Matter; Air Pollution; Livestock; Farming;

---

*Jacopo Lunghi: Bocconi University, Milan, Italy. E-mail: jacopo.lunghi@unibocconi.it

†Maurizio Malpede: University of Verona and GREEN Centre, Bocconi University, Milan, Italy. E-mail: maurizio.malpede@univr.it

‡Lara Aleluia Reis: RFF-CMCC European Institute on Economics and the Environment (EIEE), Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Milan, Italy. Email: lara.aleluia@eiee.org

Acknowledgements: This work has received funding from the Fondazione CARIPLO under the project: "INHALE - Impact on humaN Health of Agriculture and Livestock Emissions"

1 Introduction

Atmospheric particulate matter (PM) ranks as a major environmental health threat (Burnett et al. 2018), and the fourth mortality risk factor worldwide. In 2019, according to the HIME database,[1] 1 in 9 death worldwide were caused by fine particulate matter ($PM_{2.5}$) and ozone (O_3) air pollution, with the former contributing to such outcome by more than 94% (Murray et al. 2020). By threatening human welfare through poor air quality, PM also implies a large morbidity burden on the individuals: exposure to high PM levels has been associated with increased incidence of respiratory and cardiovascular diseases, such as asthma, pneumonia, hypertension, and diabetes (Dominici et al. 2006, Feng et al. 2016, Mannucci et al. 2019).

While there exists a large amount of literature focusing on the effects of industrial activities and motor-vehicle traffic on air pollution and health, the empirical evidence about the effects of farming on the concentration of human-threatening pollutants is relatively scarcer (Anenberg et al. 2019, Gibson & Carnovale 2015, He et al. 2019). Indeed, livestock farms are a key contributor to PM emissions (De Pue & Buysse 2020): animal husbandry operations are responsible for large releases of NH_3, a gaseous alkaline compound that serves as a precursor in secondary particle formation resulting from reactions with other compounds, such as sulfur oxides (SO_x) and nitrogen oxides (NO_x), ultimately representing part of the inorganic composition of $PM_{2.5}$. In turn, air pollution from livestock farms is associated with airway obstruction diseases and severe pneumonia (Borlée et al. 2017, Kalkowska et al. 2018). In the Italian case, the emission inventory of the Lombardy environmental agency INEMAR (consulted on 16/09/2020) estimates that as much as 97% of all ammonia emissions originate from farming activities in the Italian Po-valley region. Since 2005, Italy has achieved great success in reducing NO_x and SO_2 emissions from major sources such as road traffic, residential heating, and industry (Marco et al. 2019). Yet, actions in the agriculture sector have been less consistent, and PM levels remain high compared to the rest of Europe, especially in Lombardy. This highlights the crucial role of NH_3 air pollution control policies.

While the detrimental role of livestock presence in the absence of efficient air pol-

[1]http://ghdx.healthdata.org/gbd-2019

lution control practices on air quality is documented in the literature (McDuffie et al. 2021), the marginal contribution of the different species of farming animals to ammonia and subsequent PM concentrations is still poorly understood. The emission factor of a farming animal can vary considerably, depending, among others, on the specie, animal characteristics, facility type, and manure removal system. As such, different measurement methodologies and experimental settings have resulted in a vast range of possible emission factors attributable to a single unit. By reviewing multiple approaches and studies, Hristov et al. (2011) find emission factors from cows varying from 0.82 to 250 g ammonia per day. In a similar effort, Philippe et al. (2011) reported the same value for swine to be between 0.38 to 27.2 g per day. However, there have been limited efforts to measure the impact of animals on ammonia and PM levels on a significant scale. Roman et al. (2021), which looks at PM emissions particulate emission from animal farming rather than concentrations, find higher values in rural areas compared to urban areas, and that the contribution of animal farming to PM emissions varied significantly across different regions in Poland. Spencer & Van Heyst (2018) provides a review of the literature on PM emissions resulting from different sources in Canadian agricultural and rural areas. The study found that PM emissions from agricultural and rural sources, including animal farming, can contribute to elevated PM concentrations in these areas and negatively impact human health. Livestock intensity changes can be attributed to concentration, which has a direct impact on human exposure and health, unlike emissions-specific factors.

In this paper, we approach the problem of quantifying livestock-originating concentration from a broader perspective. We employ a fixed-effects spatial model which builds on exogenous high-frequency variation in wind direction and detailed data on farming animals' movements across the Lombardy region in Italy to estimate the marginal impact of two animal kinds (cattle and swine) on ammonia and PM_{10} levels observed at the municipality level. Lombardy offers a particularly suitable setting for the analysis: in addition to providing publicly available high-frequency information on pollutants and weather conditions through a granular network of sensors, it is one of the most farming-intensive regions in Europe, with more than 1 million live cattle and 4 million live swine head (see Figure 1), resulting in frequent movements of animals in and out. We take advantage of this variability to accurately identify the impact of farming on the concentration of pollutants. We access daily observations from 12 ammonia monitoring stations and 75 PM_{10} measuring points. For three stations, we obtain PM chemical decomposition data that allows us to isolate the share of ammonium sulfates (AS) and ammonium nitrates (AN), two inorganic salts that are part of the secondary PM share and are directly associated with the NH_3 precursor. We combine this data with daily weather conditions and monthly fluctuations in livestock units. We use variation in animal heads occurring in the upwind quadrant of a given sensor to estimate the marginal impact of farming animals on the levels of ammonia and PM_{10} recorded at the station level. Using variation in wind direction allows our specification to cope with possible measurement error at the station level, as well as potentially endogenous movements in livestock units induced by air pollutants. Indeed, conditional on observables and fixed effects, in order to identify the causal impact of farming animals on pollutant levels, our specification crucially rests on the assumption of orthogonality between livestock allocation decisions, weather conditions, and air quality considerations.

We find that increasing upwind cattle and swine presence by 1000 units respectively raises ammonia levels by 0.332 $\mu g/m^3$, around roughly 1.8% variation from mean concentrations, and 0.04 $\mu g/m^3$, around 0.26% with respect to mean concentrations. This appears to reflect an increase in PM10 levels, which respectively go up by 0.289 $\mu g/m^3$ and 0.04 $\mu g/m^3$. Focusing on the ammonium salts compound part of PM, given the sizeable reduction in sample size, while coefficients remain positive and strong in magnitude, standard errors increase, implying a loss in significance.

The estimated impact of farming animals is robust to different weighting schemes of animals based on distance from the closest station, as well as accounting for shifts in animal stocks being fully realized with a higher probability by the end of each month. Exploring the heterogeneity of our estimates across wind directions, we find a marginally larger effect for wind flowing from the North of the region, possibly explained by the latter being generally associated with better air quality and, in turn, a lower presence of pollutants from other sources. The effect is also found to be relatively stable across sensors.

Using our estimates, we then simulate average daily levels of PM_{10} under the counterfactual stylized scenario of no livestock units around a sensor. We find a simulated percentage reduction in daily concentrations of up to 25%. While negatively correlated with average daily levels of particulate matter, the drop in concentrations under our counterfactual simulation still emerges as a sizeable improvement in daily air quality for many densely populated areas.

Our results differ in nature from those retrieved in micro-level studies, as the primary aim is at quantifying the average relative contribution of livestock animals to station-level recorded concentrations of pollutants rather than quantifying emissions in terms of mass and differentiating for animal characteristics. Previous studies on the impacts of livestock on air quality focus mainly on emissions (Hristov 2011, INEMAR consulted on 16/09/2020, Kabelitz et al. 2020, Roman et al. 2021), and those going beyond emissions used averaged emission factors derived from the emissions studies (Pue et al. 2019, Rao et al. 2017). At a later stage, the most completed ones would then use source-receptor models or chemical transport models to derive concentrations and ultimately exposure (Lelieveld et al. 2015, McDuffie et al. 2021). As such, this research adds to the existing literature by estimating the contribution of different animal species on the levels of harmful pollutants in a highly polluted and livestock-dense area of Europe, a topic often overlooked in comparison to the livestock contribution to greenhouse gas emissions (Kipling et al. 2019*a*,*b*, Garnett 2009). The paper aims to establish a necessary step to evaluate the nature of the direct correlation between changes in livestock levels and the impact on human health due to air pollution. The use of causal inference methods is a novel approach to this type of analysis, and our findings are functional to policymakers' informed decisions regarding farming practices and air pollution control measures.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 details the empirical strategy employed, and Section 4 reports the main estimation results. Section 5 explores effect heterogeneity, while Section 6 presents a counterfactual calculation of pollutants concentrations and policy considerations following the evidence at hand. Finally, Section 7 concludes.

2 Empirical Analysis

To estimate the marginal contribution of a single farming animal to ammonia concentrations, we estimate the following regression:

$$Y_{i,t} = \beta_0 + \sum_{j \in \mathcal{B} \, \cap \, \mathcal{G}} \sum_{a \in A} \beta_a \Delta L_{a,j,t} \times \mathbf{\Omega} + X'_{i,t}\Gamma + \Lambda_{i,t,d} \tag{1}$$

where the outcome variable is ammonia concentrations (NH_3), overall particulate matter (PM_{10}) and mass concentration of ammonium sulphates and nitrate (PM_{10}^{ASN}), measured daily by station i at time t. The set $\mathcal{B}$ is defined as

$$\left\{ j \in \mathcal{B} : d_{ij} < \bar{r} \right\}$$

and contains municipalities within $\bar{r}$ distance from municipality i. We alternatively consider 50km and 60km centroid-distance as the two values of $\bar{r}$. The set $\mathcal{G}$ is instead defined as

$$\left\{ j \in \mathcal{G} : \angle ij, t \in \mathrm{WD}_{i,t} \right\}$$

and includes all municipalities which are in the same quadrant of the direction from which wind originates as measured in municipality i at time t ($\mathrm{WD}_{i,t}$). We consider four quadrants: North (315 - 45), East (45 - 135), South (135 - 225), and West (225 - 315). Thus, for each station, we obtain a time-specific total variation in the number of livestock units (ΔL), calculated as the sum of variations at the municipal level for all municipalities that are located in the quadrant of wind direction at time t and within distance $\bar{r}$ from the station. The set A includes instead the farming animals for which monthly flows are available (cattle, pigs).

ΔL is the net sum of inflows and outflows of animals (both within the region and from and to other regions and countries), births, and slaughters at the municipal level. This variation is only available at the monthly level, while ammonia levels and weather conditions are measured daily. Given the impossibility of exactly pinpointing the day of the variation in farming animals' headcount, we test the robustness of the results by applying a set of analytic weights to magnify the weight of observations occurring toward the end of the month. This is justified by thinking that, during the last days of each month, the movements depicted with monthly frequency in the data are more likely to be fully realized. Specifically, observations on the first day of the month are assigned a weight of 1/30, while observations on the last day of each month are assigned weight 1, with other observations in between weighted accordingly.

$\mathbf{\Omega}$ is a matrix of weights based on the distance between municipalities. This is motivated by assuming that the impact on ammonia levels of animals that are in closer proximity to the station will be stronger than that of animals further away, as dispersion of emissions during transportation will be less likely to occur. As such, $\mathbf{\Omega}$ partially discounts the variation happening further away from each station. In our baseline specification, Ω is simply an all-ones matrix (i.e. no discounting implied). We then test the robustness of our results by populating $\mathbf{\Omega}$ with linear and Gaussian distance weights[2]. $\mathbf{X}$ is a matrix of weather controls, including temperature, rainfall, radiance, wind speed, humidity, and boundary layer height, up to the third lag and interacted with each other. Finally, $\Lambda_{i,t,d}$ is a matrix of fixed effects, including month-by-year, sensor-by-quadrant fixed effects.

To be able to identify the marginal effect of a single livestock unit, the variation in the number of animals at the municipal level should be independent of ammonia levels and PM levels. If farmers were to time their buying, selling, and slaughtering decisions based on air quality, this could induce a reverse causality bias, inducing bias in our results. Despite the absence, in the current regulatory framework of Lombardy, of policies aimed at curbing livestock presence as a function of pollution levels, even assuming that part of farmers' decision concerning animal net flows is indirectly correlated with air quality, the use of wind direction to mediate the source of variation in livestock units allows us to restore exogeneity in the estimates. Indeed, in our specification, it is enough to assume non-

[2]Linear weights are computed as in Equation 2:

$$w_j = 1 - \frac{d_{ij}}{\bar{r}} \tag{2}$$

while Gaussian weights obey to Equation 3

$$w_j = \begin{cases} 0 & \text{if } \ d_{ij} \geq b \\ \exp\left(\frac{1}{2}\left(\frac{d_{ij}}{\bar{r}}\right)^2\right) & \text{if } \ \frac{\bar{r}}{\sqrt{2}} \ln\left(2\pi^{-\frac{1}{2}}\right) < d_{ij} < \bar{r} \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

adapting behavior from farmers to wind flows i.e., animal stock decision being independent from observed and expected wind flows. In addition, the presence of station-specific trend fixed effects allows differentiating part of the confounding variation that may be related to more polluted areas with relatively more frequent animal displacement.

Conditional on observables and fixed effects, we also argue against the likelihood of our results being driven by the presence of omitted variable bias. While we can look separately at the fluctuations in the concentration of the two among the most important farming animals in terms of pollutants contribution, the absence of data available on the movements of other animals, particularly in poultry levels, may be especially concerning, being this the third major specie in terms of air pollutants contribution.[3] Our fixed effects structure extensively controls for place-specific and time-specific events, but some variations in our measure of animal headcount at the municipal level may co-vary with the unobservable variation in the number of other farming animals (especially in the case of multi-breed farms) whose effect, in turn, would be wrongly imputed to variation in cattle and swine units alone, biasing the estimator.

However, we notice in Figure A.2.2 that the share farms specializing in more than one animal is relatively small. Farms whose production includes at least two species between cattle, chickens, and swine are less than 1% of all breeders, with the share of farms breeding all three animals being less than 0.2%. This is partially confirmed by observing that variation in the number of cattle and pigs units at the municipal level does not correlate[4]. Moreover, poultry farming appears to be more concentrated, with a relative density of more than 19,000 animals per farm, the same figure being 103 for cattle and 544 for swine. Thus, while it is not possible to fully rule out the possibility of noise induced by the absence of comprehensive data on all farming animals, the low likelihood of correlated shocks reduces importantly the concern of omitted variable bias, reinforcing our assumption.

Finally, our model implies linearity in the effect of livestock intensity. This assumption simplifies the intricate process of PM formation through secondary aerosol via chemical

[3]While the emission factor of hen is importantly lower than cattle and swine, data from INEMAR quantify poultry total particulate matter emissions in the Lombardy region at 438.9 tons, with the same number for cattle and swine being respectively 358.6 and 739.4 tons. The contribution of other animals (ovine, equine) is marginal. No disaggregated data on ammonia emissions are currently available.

[4]Spearman index: 0.02

reactions with ammonia, which can lead to non-linear effects at varying concentrations. Amid this simplifying assumption, our model serves as a valuable reference point, as it enables us to analyze the overall contribution of livestock under minimal computing and modeling requirements.

3 Data description

We access publicly available data on NH_3 and PM_{10} concentration levels and weather conditions in the Lombardy region from ARPA Lombardia[5]. We focus on years between 2015 and 2020 to match the frequency of livestock data[6]. Hourly concentration data is available for at least 365 days for 12 NH_3 stations and 75 PM_{10} stations. For a subset of stations (Schivenoglia, Milano Pascal, Milano Senato), for a total of 3299 sensor-day combinations available, we obtain information on the mass concentration of ammonium nitrates and ammonium sulfates, two compounds that enter the composition of PM_{10} and require ammonia to form. In Lombardy, the share of ammonium salts on the total PM mass can be higher than 50% (Lanzani et al. 2020). To match weather covariates, we compute average daily ammonia and PM concentrations. We obtain a final dataset of 16577 day-station-wind direction observations for NH_3, 109663 observations for PM_{10}, and 3299 observations for decomposed AS and AN. Summary statistics on pollutants are reported in Table 1, Panel A. Especially for PM concentrations, variation within the same sensor appears to be larger, given natural seasonal fluctuations. Yet, sizeable differences across stations can be observed, particularly in the case of ammonia concentrations.

Each station is imputed weather conditions recorded at the respectively closest weather stations. We collect data on temperatures (°C), rainfall (mm), wind direction (degrees) and speed (m/s), humidity (%), and radiance (W/m^2). In addition, we collect hourly data on Planetary Boundary Layer Height (PBLH) through the ERA5 Reanalysis provided by ECMWF[7] and compute average daily values. Each of these variables directly impacts airborne pollutants concentrations. Warmer temperatures are usually associated with lower concentrations, given higher thermal dispersion. Positively correlated with temperature,

[5]Regional Agency for Environmental Protection.

[6]Not all sensors have been continuously active throughout the entire sample period. We still include stations that became active after 2015 or chased activity before 2020.

[7]The measure is provided at $0.25° \times 0.25°$ grid level.

PBLH constitutes an even more cogent measure for vertical dispersion: higher PBL implies increased dispersion capacity and is associated with lower pollutant concentrations. Similarly, increased level of rainfall reduces PM concentrations through "wet deposition".

As previously noted, wind speed and direction can affect the presence of pollutants in an area by dispersing pollution plums. With increased humidity, moisture particles grow in size to the point of "dry deposition", reducing PM10 concentrations. Finally, radiance can impact PM levels, especially through photochemical reactions. These variables are summarized in Table 1, Panel B.

To visualize the correlation between wind direction and pollutants in the region, we look at the polar plots reported in Figure 3. Lombardy's morphological territory implies lower levels of pollutants are recorded when winds flow from the Alpine arch in the Northern part of the region. In general, it is observed how the wind in the Po Valley plays an important role in dispersing pollutants and leads to lower average concentrations than the winds that flow longitudinally within the region. However, the relative frequencies of wind flowing from each quadrant, as shown in Figure 4, indicate significant variation across NH_3 stations. For instance, South-East stations are more susceptible to West and North winds, while North-West areas receive more wind from the South. Similarly, PM stations show a prevalence of West winds towards the central region, but South-East and South-West areas experience a higher probability of winds flowing respectively from the North and the East. Despite some patterns, it is observed considerable variability at the station level, which suggests that uni-directional variation induced by the same quadrant always being upwind is not a significant driver in our estimates. It is worth noting that the Po Valley, particularly Lombardy, is surrounded by mountains on three sides, which limits outward air circulation and can lead to very low winds and stable conditions, especially in winter. This condition creates the perfect environment for air pollution accumulation, making the region a pollution hotspot. The average wind speed in Milan, the largest urban area in the region, is one of the lowest in Europe, exacerbating the pollution problem.

Data on livestock presence and movements are available through the National Zootechnics Registry (*Anagrafe Nazionale Zootecnica*, ANZ) database. The registry provides monthly municipal-level data on inflows and outflows of livestock (either transferred within municipalities or acquired from and sold abroad), animal slaughtering, and births. given insufficient data on other farming species, our study focuses on two animals, namely cattle and swine, which encompasses Italian Mediterranean buffalos as well.[8] These two breeds are the primary contributors to ammonia emissions. Data on newborns for swine are incorporated into monthly inflow data, thus resulting indivisible from positive variation originating from other activities. Conversely, they can be computed separately for cattle.[9] Our analysis is concentrated on Lombardy and its three adjacent regions, namely Piemonte, Veneto, and Emilia Romagna, which includes stations situated near the borders of Lombardy. This helps us consider the presence of animals in close proximity to a station while formally being located across the region's borders. To supplement our data, we utilize the municipality-level stock of animals, which is available twice a year. This measure enables us to differentiate between areas with high livestock density and those with relatively scarce farming activities.

The municipalities included in our sample reflect the high prevalence of livestock animals in the Lombardy region, with an average of more than 1000 cattle units and 2,500 swine units per municipality. Nonetheless, both cattle and swine appear to be decreasing in the region, although the variation is still a relatively small share of the existing stock (Table 2). Figure 2 shows instead how the majority of animal husbandry activities are concentrated in the South-East area of the Po Valley, both in terms of cattle and swine breeding. This reflects both in average monthly outflows and inflows, which tend to be larger in numbers in areas more populated by farming animals (Figure A.2.1), and in consistently higher concentrations of ammonia located within areas of high livestock density (Figure 5, Panel A). Conversely, due to the more heterogeneous composition of airborne particulate matter, the spatial correlation between farming animals' presence and PM_{10} is instead blurred. Thus, we employ our empirical strategy to explore the existence and magnitude of a causal relationship between animal husbandry and air pollutants and present our findings in the next section.

[8] Data on swine is only available starting in 2016.

[9] As we are not able to separate between adult animals and calves for all species in the dataset, in the headcount, we assign to all animals a unit weight. This assumption neglects the difference in emission factors between adults and calves. We deem this strategy viable in our setting in light of the objective to quantify an aggregated impact of livestock movements on airborne pollutants in the region. In addition, given the existence of a positive correlation between adult animals and calves, this distinction is unlikely to induce bias in our estimates.

4 Results

The results of estimating Equation 1 are reported in Table 3. At the baseline, we look at variations in the number of animals not discounted by distance from the station. To enhance intuition, we present our estimates in two separate forms.

In Panel A, coefficients have been re-scaled to capture a 1000 livestock units variation at the quadrant level, which is approximately a 1% change in bovines and 0.3% change in swine with respect to the overall average quadrant-level animal density. We report the results separately for the different pollutants considered: NH_3 (Columns 1 to 3), PM_{10} (Columns 4 to 6), and ammonium compounds share of PM (Columns 7 to 9). For each outcome variable, the first two columns show respectively the estimates of β when including only the variation in cattle units and only the variation in swine units. In Panel B, we instead present standardized coefficients of the same estimated relationship. We center the variation around the mean and standard deviation of livestock units present in the neighboring quadrants. As such, one standard deviation increase represents a sizeable shock in animal heads, given the high concentration at the quadrant level.

When examining levels of ammonia concentration, all coefficients are found to be significant at least at a 5% level across different specifications. The inclusion of both variations has only a minor impact on the coefficients. A 1000-unit increase in the number of cattle upwind (Panel A) raises ammonia levels between 0.286 and 0.332 $\mu g/m^3$, resulting in a 1.8% variation from the average ammonia concentrations during the sample period. The effect of a positive variation of 1000 units in swine headcount is more modest, at around 0.04, or about 0.26% relative to the average concentrations. This can be attributed not only to lower emission factors of swine but also to the fact that swine are almost four times more prevalent in the region than cattle. The standardized coefficients reported in Panel B confirm the relatively sizeable impact of livestock variation for both species: one standard deviation increase in cattle in an upwind quadrant leads to a 1.63 to 1.51 standard deviation spike in ammonia concentration. A similar increase in swine results in a 0.85 standard deviation spike.

Looking at the same estimated effect for PM_{10}, despite PM mass concentration being almost double in size compared to ammonia, the marginal impact estimated is comparable in magnitude to the one previously obtained. Indeed, upwind 1000-units increases in cattle and swine units are expected to increase PM concentrations by respectively 0.247 to 0.289 $\mu g/m^3$ and 0.01 to 0.04 $\mu g/m^3$ (which are respectively around 0.8% and 0.03% deviations from mean concentrations). This evidence supports the validity of our empirical strategy: if our estimates had been affected by confounding factors, the impact on PM and ammonia concentrations would not necessarily be equal, as these are present in the atmosphere with varying levels of mass concentrations. However, it appears that the stronger presence of $\mathrm{NH_3}$ correlates with higher concentrations of $\mathrm{PM_{10}}$ due to the formation of secondary aerosol particles.

While we would expect the observed increase in $\mathrm{PM_{10}}$ to be attributable to ammonium nitrates and ammonium sulfates particles spurring from NH_3 gaseous emissions, the relatively different and not significant coefficients observed in Columns 7 to 9 can be explained by data on $\mathrm{PM_{10}^{ASN}}$ being available only for three stations, which implies around 3% of the entire station-day level sample for PM. Furthermore, two sensors are located in the Milan area, where pollutants from other sources are present in the highest concentration. Even when the assumptions of our empirical model are satisfied, a sizeable reduction in the sample size may violate the asymptotic properties of our estimator, implying less precise and potentially biased estimates. With these caveats in mind, it is still meaningful to notice that the main coefficients remain positive and deviate by a small amount, with respect to sample average concentrations, when compared to their counterpart estimated for ammonia and overall PM concentrations.

We then proceed to explore the robustness of our results addressing two main concerns with our empirical design. First,the variation in livestock units cannot be identified with daily frequency. As such, we repeat the estimations placing more weight on the observations of air pollutants concentrations occurring towards the end of the month, where the shift in the animal count has more likely to have been fully realized. The results obtained are comparable in magnitude and significance to our baseline estimates (Table A1.1 in Appendix).

Second, as we argued that animals further away from the sensor location may contribute differently to pollutants measurement than those located in close proximity to it, we apply different specifications of Ω, i.e. varying the distance discounting weights to the variation in livestock units. In this case, coefficients do not offer direct interpretation, as the weighting inevitably inflates the magnitude by magnifying the relevance of a one-unit increase[10]. We thus rescale coefficients to represent the effect of a one-unit increase[11], and summarize the results in Figure 6. Each weighting method calculates a corresponding distribution of the estimated coefficient by multiplying the point estimates and the simulated 1000-unit variation distribution. The median result is then marked and compared to the point estimates of the non-weighted strategy. While linear discounting affects the estimated coefficients by a more sizeable amount with respect to Gaussian weighting, different specifications of Ω lead to comparable results. The marginal effect of 1000 cattle units oscillates between 0.22 and 0.33 μ g/m^3 of NH_3, and 0.27 and 0.41 μ g/m^3 of PM_{10}. The same variation in terms of swine units provides estimates fluctuating between around 0.02 and 0.05 μ g/m^3 of NH_3, and 0.004 and 0.16 μ g/m^3 of PM_{10}.

While our analysis provides a less specific picture compared to studies that quantify emissions using ad-hoc detection strategies, these results provide a robust and new perspective on the aggregate impact of animal husbandry on concentrations of air pollutants in a region with a high density of livestock such as Lombardy. This evidence can help guide the cost-benefit analysis of expansions and reduction of livestock intensity from a policymaking perspective. To this aim, we explore heterogeneity in effect retrieved that may result in better-informed policy considerations.

5 Heterogeneity and Sensitivity

We test the sensitivity and heterogeneity of our results in two ways. First, we account for potential differential effects of livestock variation depending on the quadrant of the source. To this aim, we add a set of interactions to Equation 1, letting the marginal impact of farming animals variation vary through the source quadrant. Analytically, Equation 1 is

[10] To clarify this aspect of our weighting strategy further, we simulate a 1000-units positive variation happening around a station. Units are located at a random distance $\tilde{d}$ from the station according to a uniform distribution $\tilde{d} \sim U(0, \bar{r})$. Weighting is applied to compute the actual increase in ΔL. We plot the result of a 10,000 iterations simulation in Figure A.2.3

[11] Estimates of the weighted variation strategy are reported in Appendix, Tables A1.2, A1.3,A1.4.

expanded as follows:

$$Y_{i,t} = \beta_0 + \sum_{j \in \mathcal{B} \,\cap\, \mathcal{G}} \sum_{a \in A} \beta_a \Delta L_{a,j,t} + \sum_{j \in \mathcal{B} \,\cap\, \mathcal{G}} \sum_{a \in A} \sum_{q \in Q} \eta_a \Delta L_{a,j,t} \times D_q + X'_{i,t}\Gamma + \Lambda_{i,t,d} \quad (4)$$

where, for simplicity, we consider the absence of weighting ($\Omega = I$), and D_q is an indicator assuming value 1 when variation originates from quadrant q, zero otherwise. Note that our fixed effects structure naturally absorbs the differential intercept for each quadrant. The results are presented graphically in Figure 7. We take as reference group livestock headcount variation happening in Southern quadrants. The results highlight how movements in farming animals tend to have a larger impact on pollutants concentrations at the sensor level when they occur to the North of a station. This finding appears in line with the evidence presented in Figure 3: North winds are usually associated with lower levels of pollutants, which reduces the extent of confounding variation, particularly with respect to particulate matter. As such, fluctuations in the livestock units taking place North to a sensor will imply larger spikes in recorded levels of airborne pollutants, being this *ceteris paribus* lower at the baseline under such weather conditions. The effect appears instead to be homogeneous across other quadrants, with smaller and primarily non-significant coefficients associated with the interaction terms. Hence, while other sources of air pollutants may still induce noise in the results despite our strategy, the impact of livestock appears even magnified when the likelihood of the presence of confounders decreases.

Second, we investigate whether the effect retrieved is driven by using only a limited number of sensors. This is particularly of concern when considering ammonia levels, which are recorded consistently on a network of only 12 stations. The presence of one or few sensors reacting diametrically differently to shocks in livestock headcounts may inflate the results and cast doubt over the accuracy of our coefficients. To this aim, we iteratively repeat the estimation, keeping all but one sensor at each iteration. The new coefficients obtained through this methodology for NH_3 are plotted in Figure 8. On the horizontal axis is reported the name of the dropped station. Stations are sorted from left to right according to the number of animal units within the defined r-radius buffer. The coefficients remain relatively stable with some minor fluctuations, and most instances show significance at a 95% level. In Panel B, we also notice that only one sensor shows a noticeable fluctuation in the effect retrieved, which is located in the Corte de Cortesi municipal area. This can be attributed to the proximity of a large swine farm near the station, though we do not have a specific reference to cite. This station was purposely placed next to a large-scale swine livestock facility in order to monitor emissions from swine husbandry. Similarly, the Bertonico station is located next to a large-scale cattle husbandry area to monitor the concentrations from his sub-sector of agriculture. In turn, local fluctuations in ammonia levels originating from daily farming activities of different natures may overcast the movements in animal units taking place further away from the station, hence inducing particular noise in the estimates retrieved through our empirical strategy.[12] Nonetheless, while the coefficient decreases in magnitude when excluding the sensor from the sample, it remains positive and comparable in size.

Since the sample available for PM_{10} includes a considerably larger number of sensors, we repeat the procedure by dropping all stations in a given province (Figure 9).[13]. The results again show minor fluctuations around the average estimated effect, proving the relative stability of the effect of farming animals across the region.

6 Policy Considerations

Assessing the agricultural sector's impact on ammonia and particulate matter (PM) concentrations is crucial for policymaking in Lombardy. This region is susceptible to environmental and health threats due to its dense population, intense farming, and low wind conditions caused by its orographic features. To comprehend the implications of our findings, we propose a straightforward calculation to determine the toll that farming takes on air quality and, consequently, public health.

Our objective is to establish the impact of farming animals on air pollution levels in

[12]For instance, ammonia levels can fluctuate due to manure management practices, such as storage and disposal, or even due to the application of nitrogen-based fertilizers, which can release ammonia gas into the air. This can lead to the release of ammonia into the air, affecting local air quality. The use of litter and manure management practices can also contribute to fluctuations in local ammonia levels in poultry farming operations. Finally, the handling of dairy waste, such as urine and manure, can also lead to local fluctuations in ammonia levels.

[13]The Lombardy region is divided into 12 provinces. In brackets, the number of PM_{10} sensors per province is reported: BG (9); BS (6); CO (3); CR (6); LC (5); LO (7); MB (4); MI (11); MN (8); PV (7) SO (4); VA (5).

the surrounding sensor stations area. Using data from ISTAT data[14] to calculate the population residing within a 50km radius of the sensor stations and couple it with information on the number of livestock units within each buffer zone. We then simulate a hypothetical scenario where we remove all farming animals from each buffer zone, leveraging the coefficients we obtained from a 1000-unit variation analysis to estimate the corresponding reduction in air pollutant concentration.[15].[16]

Given that adverse health effects are associated with PM rather than gaseous ammonia alone, which instead acts as a precursor to the particulate formation, in this part of the paper we only focus on PM10 concentrations. Panel A in Figure 10 shows the results of this exercise by plotting the reduction in daily PM10 concentrations over twenty sensor bins, with the latter calculated conditioning on yearly average concentrations. Panel B plots the same reduction paired with the total resident population in each bin.

Two main considerations are in place. First, it appears that the areas with lower average daily concentrations of PM10 are more severely affected by the threat to air quality posed by livestock (Panel A). The largest reduction (approximately 25%) observed in the simulation is in sensors with an average yearly concentration of less than 30 $\mu g/m^3$. This can be attributed to the fact that areas with more farming activity generally have a lower degree of urbanization and a reduced incidence of emission factors from other industries like transportation, construction, and manufacturing. However, this also means that less urbanized areas are disproportionately burdened by the presence of livestock and are unable to fully benefit from high air quality.

Second, looking at Panel B, even in less urbanized areas that are more susceptible to air pollution from livestock sources, population density is still considerably high: nearly 7 out of 14 million people reside within 50km of those stations that would benefit from a

[14]Source: Resident Population on 1st January.

[15]This strategy once again simplifies by assuming the effect to be linear and unsusceptible to the number of livestock units already present in the area. While this may constitute a limitation to our approach, we still deem this procedure informative to approximate the true impact of the farming industry on air pollution in the region.

[16]Population and livestock headcount data are available at the municipality level. To avoid double-counting, whenever a municipality lies within a 50km radius of multiple stations, its population is imputed to different buffer zones in equal shares. The potential noise in the calculations induced by this strategy is tapered by counterfactual concentrations being computed as the mean across stations in the same decile of the distribution of yearly average concentrations. As stations in close proximity are likely to register similar yearly levels of pollutants, the population in the area is likely to be imputed the same counterfactual exposure levels regardless of whether individuals are assigned to one station or the other.

counterfactual level of PM10 concentrations below $30\mu g/m^3$ in our simulation. Furthermore, station buffers that would experience the highest percentage reduction (more than 20%) appear surrounded by almost 2 million inhabitants.[17]. These findings highlight how the estimated deterioration in air quality is likely to affect a significant proportion of the population, rather than being limited to sparsely populated rural municipalities.

Our simulations advocate for integrated policies in the agricultural sector, particularly in densely populated regions with high livestock density, like Lombardy, where the secondary formation of ammonium nitrates often reaches more than 50% of the total PM mass (Tao et al. 2016, Wu et al. 2020). It is particularly important to target concentration reduction that can effectively minimize the effects of agricultural activities. These may include the use of BATs (best available technologies, e.g. injector systems and genetic engineering) in agriculture and farming practices, improved integrated management of farming activities (such as improved animal diet, efficient disposal of slurry and manure, and efficiency in the production system), and livestock intensity (Ammann et al. 2022, OECD. 2019).

7 Conclusion

This paper estimated the marginal impact of cattle and swine farming on the levels of ammonia (NH_3) and particulate matter (PM_{10}) in the Lombardy region. We used daily observations from 12 ammonia monitoring stations and 75 PM10 measuring points and combined them with monthly fluctuations in livestock units and daily weather conditions.

The results showed that an increase in upwind cattle and swine presence by 1000 units respectively raised ammonia levels by 0.332 μg/m3 (around 1.8% variation from mean concentrations) and 0.04 μg/m3 (around 0.26% with respect to mean concentrations), and PM10 levels by 0.289 μg/m3 and 0.04 μg/m3 respectively. The results are robust to different weighting schemes and provide information on the average relative contribution of livestock to station-level recorded concentrations of pollutants.

Our simulation showed that livestock presence is expected to cause sensitive deteriora-

[17] In this calculation, we do not factor in individuals residing outside the 50km buffer zones used to obtain our estimates, as this would require a more comprehensive analysis of how pollutants are transported across the region, which is beyond the scope of this paper.

tion in air quality for a sizeable share of the region's population. Hence, the study provides insights into the potential impact of changing livestock intensity in the Lombardy region and highlights the need for further research to understand the role of livestock in air pollution. In particular, future research should focus on carefully evaluating the cost-benefit tradeoff involved by technology and organizational available alternative in the industry to prevent harmful effects on individual health and guide the evolution of the industry onto a more sustainable path.

References

Ammann, J., Umstätter, C. & El Benni, N. (2022), 'The adoption of precision agriculture enabling technologies in Swiss outdoor vegetable production: a Delphi study', *Precision Agriculture* **23**(4), 1354–1374.

Anenberg, S. C., Achakulwisut, P., Brauer, M., Moran, D., Apte, J. S. & Henze, D. K. (2019), 'Particulate matter-attributable mortality and relationships with carbon dioxide in 250 urban areas worldwide', *Scientific reports* **9**(1), 11552.

Borlée, F., Yzermans, C. J., Aalders, B., Rooijackers, J., Krop, E., Maassen, C. B., Schellevis, F., Brunekreef, B., Heederik, D. & Smit, L. A. (2017), 'Air pollution from livestock farms is associated with airway obstruction in neighboring residents', *American journal of respiratory and critical care medicine* **196**(9), 1152–1161.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope Iii, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S. et al. (2018), 'Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter', *Proceedings of the National Academy of Sciences* **115**(38), 9592–9597.

De Pue, D. & Buysse, J. (2020), 'Safeguarding Natura 2000 habitats from nitrogen deposition by tackling ammonia emissions from livestock facilities', *Environmental Science & Policy* **111**, 74–82.

URL: *https://www.sciencedirect.com/science/article/pii/S1462901119311360*

Dominici, F., Peng, R. D., Bell, M. L., Pham, L., McDermott, A., Zeger, S. L. & Samet, J. M. (2006), 'Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases', *Jama* **295**(10), 1127–1134.

Feng, S., Gao, D., Liao, F., Zhou, F. & Wang, X. (2016), 'The health effects of ambient PM2. 5 and potential mechanisms', *Ecotoxicology and environmental safety* **128**, 67–74.

Garnett, T. (2009), 'Livestock-related greenhouse gas emissions: impacts and options for policy makers', *Environmental Science & Policy* **12**(4), 491–503. Special Issue: Food Security and Environmental Change.

URL: *https://www.sciencedirect.com/science/article/pii/S1462901109000173*

Gibson, M. & Carnovale, M. (2015), 'The effects of road pricing on driver behavior and air pollution', *Journal of Urban Economics* **89**, 62–73.

He, J., Liu, H. & Salvo, A. (2019), 'Severe air pollution and labor productivity: Evidence from industrial towns in china', *American Economic Journal: Applied Economics* **11**(1), 173–201.

Hristov, A. (2011), 'Technical note: Contribution of ammonia emitted from livestock to atmospheric fine particulate matter (PM2.5) in the united states', *Journal of Dairy Science* **94**(6), 3130–3136.

Hristov, A. N., Hanigan, M., Cole, A., Todd, R., McAllister, T. A., Ndegwa, P. M. & Rotz, A. (2011), 'Ammonia emissions from dairy farms and beef feedlots', *Canadian journal of animal science* **91**(1), 1–35.

INEMAR (consulted on 16/09/2020), Principali risultati inventario 2017 (revisione pubblica), Technical report, INEMAR.
URL: *https://www.inemar.eu*

Kabelitz, T., Ammon, C., Funk, R., Münch, S., Biniasch, O., Nübel, U., Thiel, N., Rösler, U., Siller, P., Amon, B., Aarnink, A. J. & Amon, T. (2020), 'Functional relationship of particulate matter (PM) emissions, animal species, and moisture content during manure application', *Environment International* **143**, 105577.

Kalkowska, D. A., Boender, G. J., Smit, L. A., Baliatsas, C., Yzermans, J., Heederik, D. J. & Hagenaars, T. J. (2018), 'Associations between pneumonia and residential distance to livestock farms over a five-year period in a large population-based study', *PLoS One* **13**(7), e0200813.

Kipling, R. P., Taft, H. E., Chadwick, D. R., Styles, D. & Moorby, J. (2019*a*), 'Challenges to implementing greenhouse gas mitigation measures in livestock agriculture: A conceptual framework for policymakers', *Environmental Science & Policy* **92**, 107–115.
URL: *https://www.sciencedirect.com/science/article/pii/S1462901118307664*

Kipling, R. P., Taft, H. E., Chadwick, D. R., Styles, D. & Moorby, J. (2019*b*), 'Implementation solutions for greenhouse gas mitigation measures in livestock agriculture: A framework for coherent strategy', *Environmental Science & Policy* **101**, 232–244.
URL: *https://www.sciencedirect.com/science/article/pii/S146290111930214X*

Lanzani, G., D'Angelo, L., Cuccia, E., Corbella, L., Santo, U. D., Colombi, C., Algieri, A., Bravetti, E., Lazzarini, M., Gurrieri, G. L., Poluzzi, V., Ferrari, S., DimitriBacco &

Deserti, M. (2020), ‘Ammoniaca e formazione di particolato secondario’, *ECOSCIENZA* .

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D. & Pozzer, A. (2015), ‘The contribution of outdoor air pollution sources to premature mortality on a global scale’, *nature* **525**, 367—371.
URL: *https://doi.org/10.1038/nature15371*

Mannucci, P. M., Harari, S. & Franchini, M. (2019), ‘Novel evidence for a greater burden of ambient air pollution on cardiovascular disease’, *haematologica* **104**(12), 2349.

Marco, A. D., Proietti, C., Anav, A., Ciancarella, L., D'Elia, I., Fares, S., Fornasier, M. F., Fusaro, L., Gualtieri, M., Manes, F., Marchetto, A., Mircea, M., Paoletti, E., Piersanti, A., Rogora, M., Salvati, L., Salvatori, E., Screpanti, A., Vialetto, G., Vitale, M. & Leonardi, C. (2019), ‘Impacts of air pollution on human and ecosystem health, and implications for the national emission ceilings directive: Insights from Italy’, *Environment International* **125**, 320–333.

McDuffie, E. E., Martin, R. V., Spadaro, J. V., Burnett, R., Smith, S. J., O’Rourke, P., Hammer, M. S., van Donkelaar, A., Bindle, L., Shah, V., Jaeglé, L., Luo, G., Yu, F., Adeniran, J. A., Lin, J. & Brauer, M. (2021), ‘Source sector and fuel contributions to ambient PM2.5 and attributable mortality across multiple spatial scales’, *Nature Communications* **12**(1).

Murray, C. J., Aravkin, A. Y., Zheng, P., Abbafati, C., Abbas, K. M., Abbasi-Kangevari, M., Abd-Allah, F., Abdelalim, A., Abdollahi, M., Abdollahpour, I. et al. (2020), ‘Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the global burden of disease study 2019’, *The lancet* **396**(10258), 1223–1249.

OECD. (2019), *Digital opportunities for better agricultural policies*, OECD.

Philippe, F.-X., Cabaraux, J.-F. & Nicks, B. (2011), ‘Ammonia emissions from pig houses: Influencing factors and mitigation techniques’, *Agriculture, ecosystems & environment* **141**(3-4), 245–260.

Pue, D. D., Bral, A. & Buysse, J. (2019), ‘Abatement of ammonia emissions from livestock housing fine-tuned according to impact on protected habitats’, *Agricultural Systems*

176, 102667.

Rao, S., Klimont, Z., Smith, S. J., Dingenen, R. V., Dentener, F., Bouwman, L., Riahi, K., Amann, M., Bodirsky, B. L., van Vuuren, D. P., Reis, L. A., Calvin, K., Drouet, L., Fricko, O., Fujimori, S., Gernaat, D., Havlik, P., Harmsen, M., Hasegawa, T., Heyes, C., Hilaire, J., Luderer, G., Masui, T., Stehfest, E., Strefler, J., van der Sluis, S. & Tavoni, M. (2017), 'Future air pollution in the shared socio-economic pathways', *Global Environmental Change* **42**, 346–358.

Roman, M., Roman, K. & Roman, M. (2021), 'Spatial variation in particulate emission resulting from animal farming in Poland', *Agriculture* **11**(2), 168.

Spencer, J. & Van Heyst, B. (2018), 'A review of particulate matter emissions and impacts on human health: A focus on Canadian agricultural and rural emission sources', *Canadian Biosystems Engineering/Le génie des biosystèmes au Canada* **60**, 6–9.

Tao, Y., Ye, X., Ma, Z., Xie, Y., Wang, R., Chen, J., Yang, X. & Jiang, S. (2016), 'Insights into different nitrate formation mechanisms from seasonal variations of secondary inorganic aerosols in Shanghai', *Atmospheric Environment* **145**, 1–9.

Wu, C., Zhang, S., Wang, G., Lv, S., Li, D., Liu, L., Li, J., Liu, S., Du, W., Meng, J. et al. (2020), 'Efficient heterogeneous formation of ammonium nitrate on the saline mineral particle surface in the atmosphere of East Asia during dust storm periods', *Environmental science & technology* **54**(24), 15622–15630.

Tables

Table 1: Descriptive statistics - Pollutants and Weather

	Overall	Within	Between
Panel A - Pollutants			
NH_3	15.74		
(μg/m^3)	(19.97)	(14.06)	(12.84)
	[0.0 ; 430.6]	[-29.1 ; 429.2]	[3.0 ; 45.4]
PM_{10}	30.61		
(μg/m^3)	(20.70)	(19.99)	(5.15)
	[0.0 ; 264.0]	[-10.0 ; 264.4]	[13.0 ; 41.6]
PM_{10} (AS + AN)*	10.95		
(μg/m^3)	(10.78)	(10.77)	(0.57)
	[0.0 ; 58.3]	[0.0 ; 58.7]	[10.5 ; 11.7]
Panel B - Weather			
Temperature	13.87		
(° C)	(8.25)	(8.12)	(1.41)
	[-11.3 ; 32.7]	[-7.1 ; 31.4]	[9.7 ; 15.3]
Rainfall	0.05		
(mm)	(2.19)	(2.19)	(0.04)
	[0.0 ; 256.8]	[-0.1 ; 256.8]	[0.0 ; 0.1]
Wind Speed	1.97		
(m/s)	(0.95)	(0.92)	(0.30)
	[0.0 ; 26.3]	[-0.4 ; 26.4]	[1.5 ; 2.6]
Wind Direction	176.01		
(Degree)	(97.61)	(95.62)	(21.82)
	[0.1 ; 360.0]	[-28.8 ; 404.2]	[131.8 ; 205.0]
Radiance	161.25		
(W/m^2)	(103.94)	(103.64)	(8.12)
	[0.0 ; 517.6]	[-18.4 ; 528.7]	[150.2 ; 179.6]
Humidity	73.22		
(%)	(16.83)	(16.17)	(4.85)
	[0.0 ; 100.0]	[-2.1 ; 107.1]	[65.5 ; 79.9]
PBLH	1,654.82		
(m)	(1,415.71)	(1,412.01)	(100.24)
	[11.4 ; 5,553.5]	[-127.5 ; 5,543.8]	[1,439.3 ; 1,803.9]

Notes: the table reports summary statistics for pollutants (A) and weather variables (B). Mean values are presented first, both within the same sensor across time and between sensor and overall mean. Parentheses include standard deviations, brackets report minimum and maximum values.
Source: ARPA Lombardia, ECMWF.

Table 2: Descriptive statistics - Livestock

	Cattle			Swines		
	Overall	Within	Between	Overall	Within	Between
Inflow*	13.84			456.75		
(monthly)	(59.43)	(57.55)	(16.11)	(1,429.43)	(1,348.00)	(565.28)
	[0.0 ; 1,663.0]	[-37.0 ; 1,641.0]	[0.8 ; 50.9]	[0.0 ; 23,932.0]	[-967.8 ; 23,342.1]	[1.9 ; 1,424.5]
Births**	43.39			-		
(monthly)	(88.57)	(80.46)	(42.84)	-	-	-
	[0.0 ; 1,379.0]	[-74.4 ; 1,362.2]	[8.9 ; 117.8]	-	-	-
Outflow	-6.61			-450.06		
(monthly)	(30.35)	(29.91)	(6.02)	(1,650.23)	(1,583.29)	(547.31)
	[-1,201.0 ; 0.0]	[-1,197.3 ; 10.2]	[-16.8 ; -0.5]	[-20,431.0 ; 0.0]	[-19,957.8 ; 994.5]	[-1,444.6 ; -0.7]
Slaughters	-57.16			-370.86		
(monthly)	(190.71)	(179.90)	(74.50)	(1,044.20)	(980.95)	(412.65)
	[-3,643.0 ; 0.0]	[-3,511.9 ; 137.0]	[-194.2 ; -5.2]	[-14,064.0 ; 0.0]	[-13,575.4 ; 631.7]	[-1,002.6 ; -1.5]
Net variation	-262.63			-415.14		
(monthly)	(4,719.15)	(3,977.39)	(3,035.25)	(433.52)	(263.28)	(384.11)
	[-20,706.0 ; 9,072.0]	[-16,007.1 ; 13,482.5]	[-7,324.1 ; 2,386.3]	[-18,574.10 ; 10,742.0]	[-14,710.72 ; 53,331.7]	[-10,574.50 ; -11.2]
Tot animals	137,984			320,928		
(quadrant)	(139,002)	(91,009)	(117,959)	(430,301)	(320,167)	(291,739)
	[2,204.25 ; 497,245]	[-170,965.74 ; 351,963]	[13,925.67 ; 326,303]	[0.00 ; 1,642,738]	[-552,364.85 ; 1,448,462]	[1,117.73 ; 873,293]
Tot animals	1,088			2,533		
(municipality)	(2,382)	(197)	(2,318)	(7,655)	(1,102)	(7,189)
	[1.00 ; 35,915]	[-5,255.98 ; 4,957]	[1.00 ; 34,079]	[0.00 ; 94,944]	[-16,040.20 ; 34,015]	[0.00 ; 85,873]

Notes: the table reports summary statistics for livestock variables. Mean values are presented first, both within the same sensor across time and between sensor and overall mean. Parentheses include standard deviations, brackets report minimum and maximum values.
* Inflow and outflow variables include animal movements taking place between facilities within and outside the region.
** Data on newborns for swine are incorporated into the provided measure for monthly inflow by the data provider, and cannot be accessed separately.
Source: National Zootechnics Registry.

Table 3: Baseline Estimates

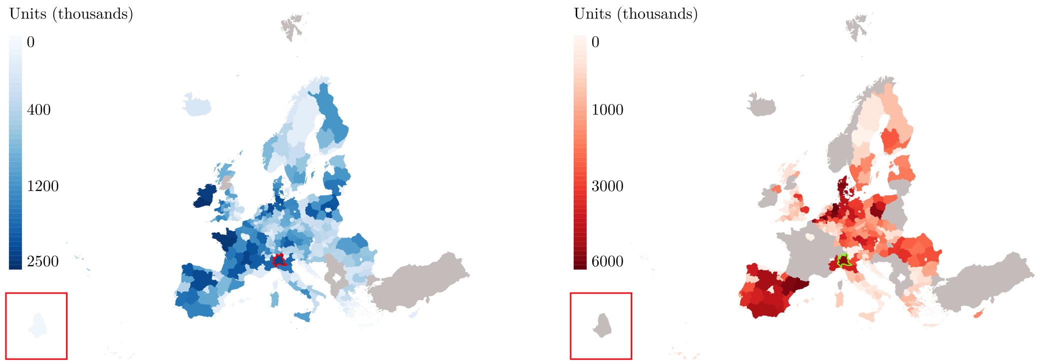
	NH_3			PM_{10}			PM_{10}^{ASN}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A] - $\Delta 10^3$-units									
Δ - Cattle	0.332***		0.286**	0.247***		0.289***	0.118		0.150
	(0.106)		(0.112)	(0.052)		(0.052)	(0.13)		(0.14)
Δ - Pig		0.040**	0.0403***		0.004	0.0099***		0.014	0.0147
		(0.016)	(0.016)		(0.003)	(0.003)		(0.02)	(0.02)
Panel B]									
Δ - Cattle	1.63***		1.51**	1.38***		1.62***	1.01		1.28
	(0.66)		(0.69)	(0.29)		(0.29)	(1.12)		(1.18)
Δ - Pig		0.84**	0.85***		0.08	0.2123***		0.30	0.3230
		(0.36)	(0.36)		(0.06)	(0.06)		(0.42)	(0.41)
Observations	16579	13919	13919	109202	109650	109650	3299	2790	2790
Adj R^2	0.5767	0.5694	0.5698	0.5144	0.5143	0.5146	0.5061	0.5109	0.5114
Dep. Var. Mean	15.53	15.53	15.53	30.42	30.42	30.42	10.68	10.68	10.68
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sensor-by-quadrant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: the table reports the estimates of β_a from Equation 1, where Ω is an identity matrix (absence of distance weighting). Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average planetary boundary layer height, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figures

Figure 1: Livestock presence - Eurostat NUTS2 level

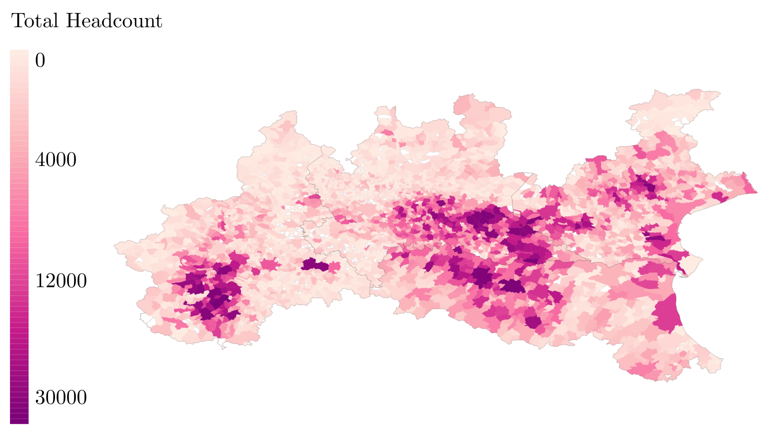
[A] - Cattle [B] - Swine



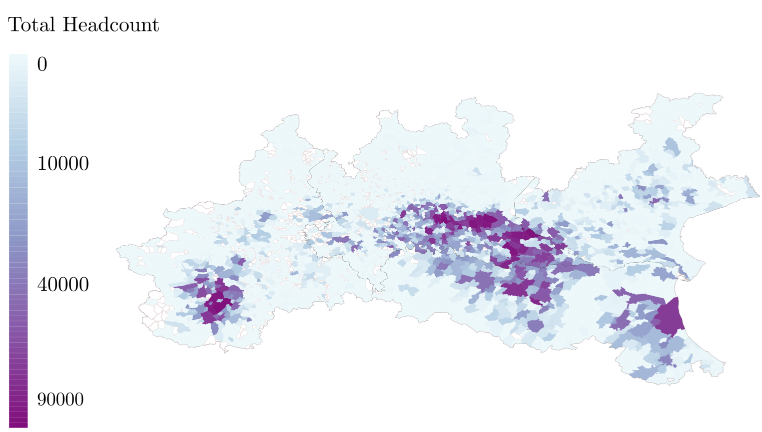
Notes: the figure reports live cattle (Panel A) and swine animals (Panel B) across European NUTS 2 regions. The Lombardy region (framed) is the 14th area in terms of absolute units of bovine in Europe, 8th in terms of swine absolute units. Units are reported to the most recent data point available (2020 for bovine, 2016 for swines).
Source: Eurostat.

Figure 2: Animals total headcount

[A] - Cattle



[B] - Swine



Notes: the figure reports the sample average total headcount of cattle (Panel A) and swines (Panel B) at municipal level across four regions: Lombardy, Piedmont, Emilia-Romagna, and Veneto. The regions' area cover all municipalities located within a 60km radius from at least one NH_3 or PM station.

Figure 3: Wind direction frequencies - sample average

[A] [B]

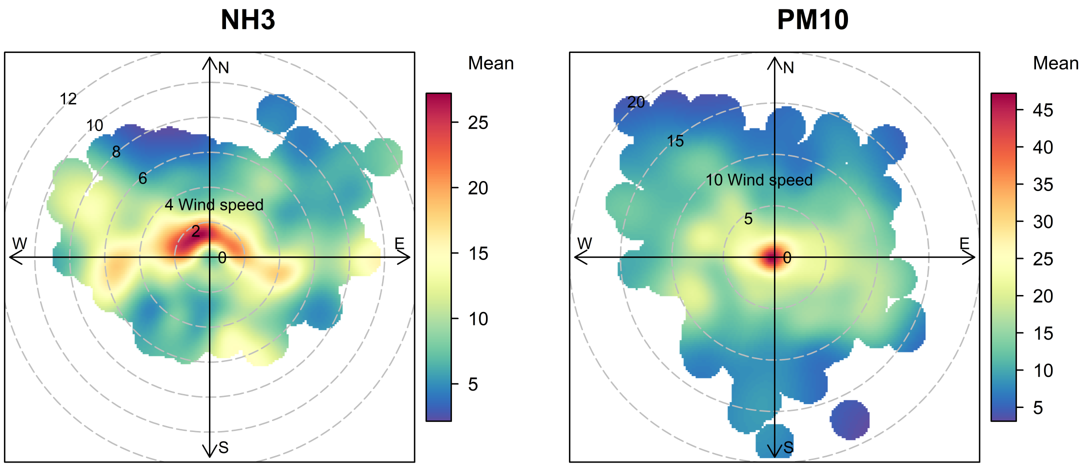
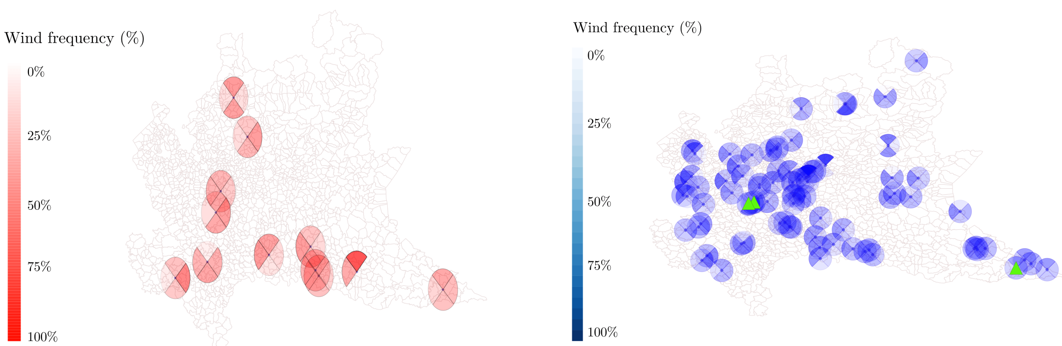


Figure 4: Wind direction frequencies - sample average

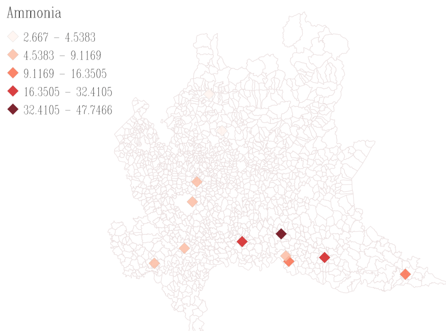
[A] - NH_3 Buffers [B] - PM_{10} Buffers



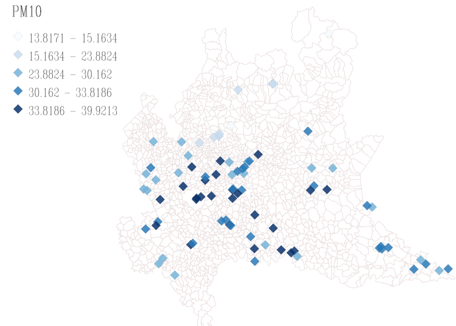
Notes: the figure reports quadrant-specific wind frequency at station level, calculated as the number of days recording wind flowing from a given quadrant over the entire sample period (2015-2020). Panel A plots wind frequencies for ammonia stations, while Panel B plots the same statistics for PM10 stations. Triangles in Panel B mark sensor that provide decomposed data on ammonium nitrates and ammonium sulphates.

Figure 5: Pollutants concentration - sensor sample average

[A] NH_3



[B] PM_{10}

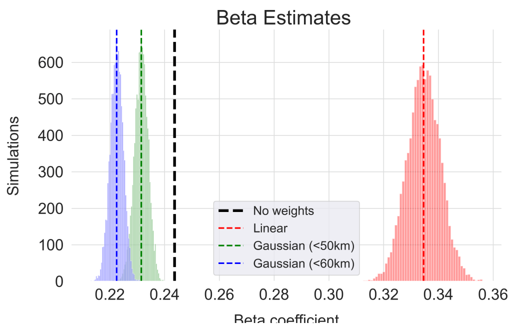


Notes: the figure plots ammonia (Panel A) and PM stations in Lombardy. Column size is determined by average daily concentration ($\mu g/m^3$ throughout the year at sensor level. Max - Min values: [2.7; 47.7] Panel A; [13.8; 39.9] Panel B.

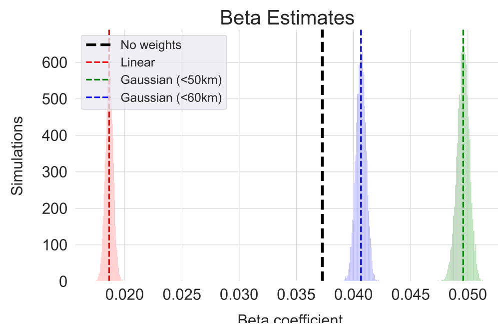
Figure 6: Distributions of simulated weighted variation in livestock units (quadrant)

[I] NH_3

[A] Cattle

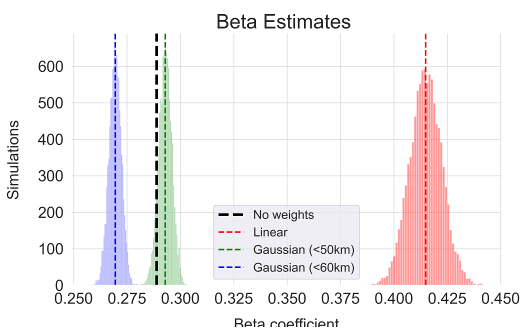


[B] Swine

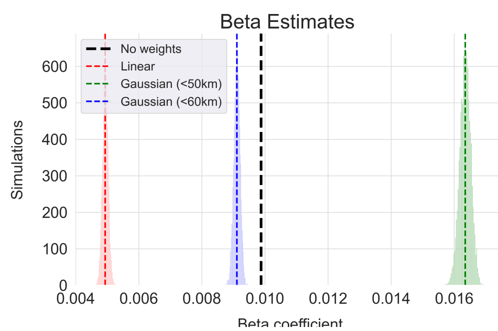


[I] PM_{10}

[A] Cattle

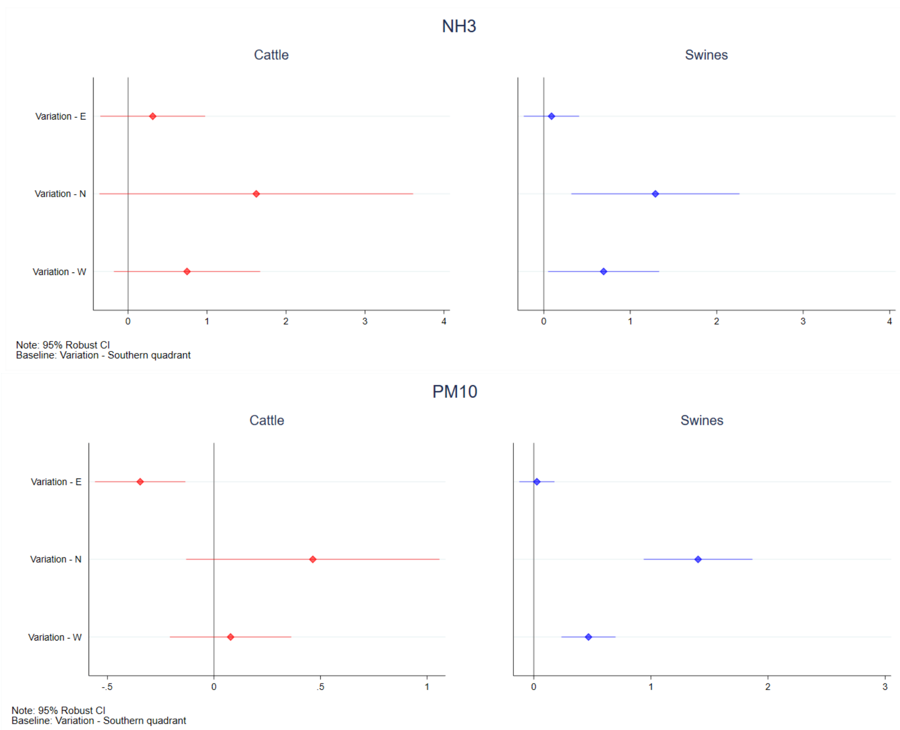


[B] Swine



Notes: the figure compares the marginal contribution of a 1000-units positive variation estimated without distance discounting weighting with that obtained through different specifications of Ω. Estimates are presented separately by pollutant (Panels I to III) and farming animal (Panel A and B). Coefficients are estimated according to Equation 1, while Ω weights are computed according to Equations 2 and 3. The resulting effect plotted in the graph is obtained by multiplying point estimates (See Appendix, Tables A1.1 through A1.4) and the simulated 1000-units variation distribution.

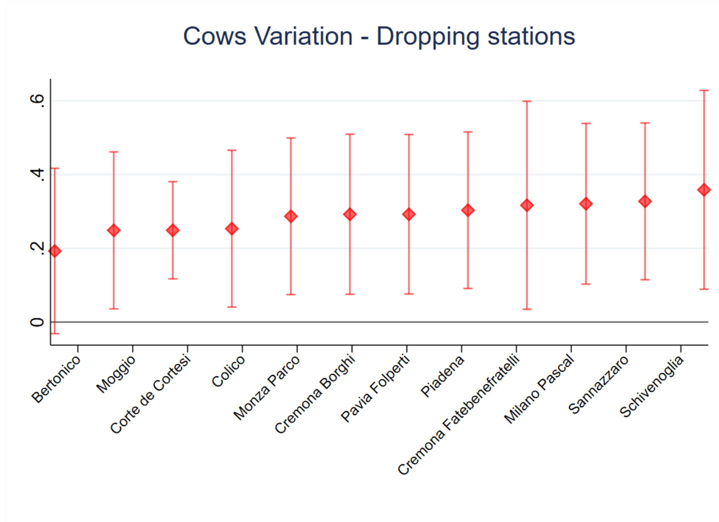
Figure 7: Effect heterogeneity - Wind direction



Notes: The table reports the estimates of η_a coefficients from Equation 4. Control group is the variation in livestock units taking place in the quadrant South of each sensor. Weather controls (temperature, wind direction, wind speed, rainfall, radiance, humidity, average planetary boundary layer height, interacted with each other up to three lags) and month. year, station-by-quadrant fixed effects are included. Robust confidence intervals at 95% are plotted.

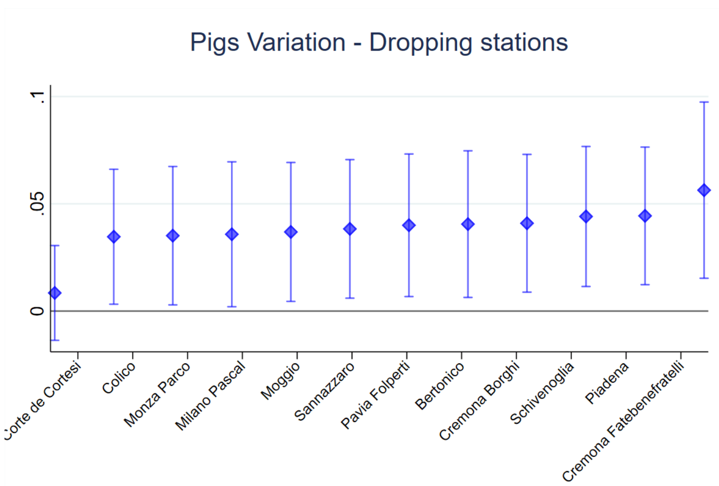
Figure 8: Effect heterogeneity - Dropping NH_3 stations

[A] - Cattle



Station	*Cattle (Buffer avg.)*
Cremona Borghi	1297819
Piadena	1265482
Cremona Fatebene	1053679
Corte de Cortesi	1030262
Bertonico	877854
Schivenoglia	712969
Milano Pascal	402840
Monza Parco	395167
Pavia Folperti	365971
Moggio	203124
Sannazzaro	153805
Colico	53738

[B] - Swine

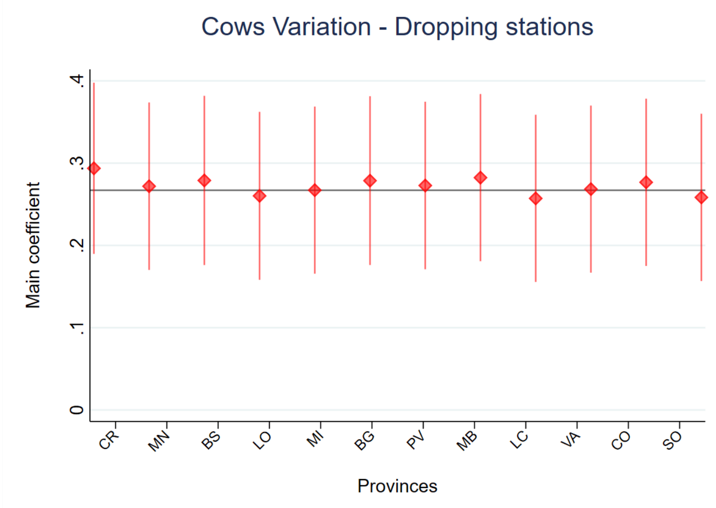


Station	*Swine (Buffer avg.)*
Corte de Cortesi	3954152
Cremona Fatebene	3779251
Cremona Borghi	3690717
Piadena	3633510
Bertonico	2946117
Schivenoglia	1967174
Milano Pascal	989238
Monza Parco	929888
Pavia Folperti	828486
Sannazzaro	433970
Moggio	319311
Colico	7421

Notes: The figure plots the estimates of β_a from Equation 1, with $\Omega = I$, when observations from the sensor reported on the horizontal axis are excluded from the sample. Horizontal lines in Panel A and B correspond to the coefficients estimated in Table 3, Column 3. In the table, the sample average number of animal per station buffer is reported.

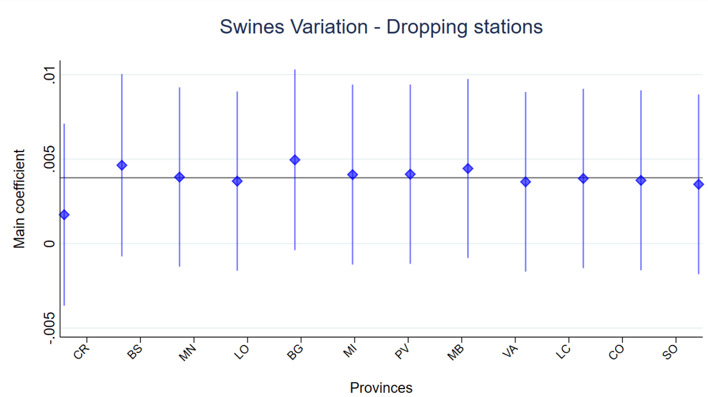
Figure 9: Effect heterogeneity - Dropping NH_3 stations

[A] - Cattle



Station	*Cattle (Buffer avg.)*
MN	49498.51
CR	38685.26
LO	30789.42
BS	27381.61
BG	23418.84
MI	12662.75
PV	8613.302
LC	4849.589
MB	4355.362
VA	4065.111
SO	3246.571
CO	3163.018

[B] - Swine

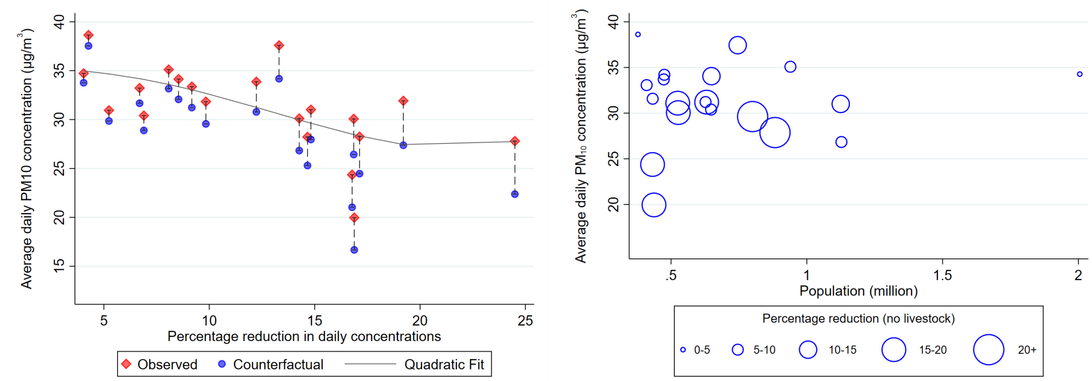


Station	*Swine (Buffer avg.)*
MN	181736.6
CR	120776.5
BS	109817.4
LO	101199.3
BG	80343.15
MI	33902.45
PV	20898.13
MB	10134.75
LC	8952.52
VA	6564.874
CO	3621.552
SO	488.6933

Notes: The figure plots the estimates of β_a from Equation 1, with $\Omega = I$, when observations from the sensor reported on the horizontal axis are excluded from the sample. Horizontal lines in Panel A and B correspond to the coefficients estimated in Table 3, Column 3. In the table, the sample average number of animals per station buffer is reported.

Figure 10: Counterfactual PM levels and population exposure

[A] Reduction in PM levels   [B] Population affected



Notes: the figure shows the counterfactual scenario simulating the absence of bovine and swine livestock units. For visual purposes, sensors are grouped into twenty bins, calculated conditioning on yearly average concentrations. Panel A shows the relationship between average daily concentration and corresponding percentage reduction under the absence of swine and cattle units scenario. Panel B relates reduction under the counterfactual scenario with the population residing within a 50km radius of the sensors. Marker's size varies with the calculated percentage reduction in PM_{10} in the absence of livestock units.

Appendix

A1.Appendix Tables

Table A1.1: Estimates Robustness - Probability weighting

	NH_3			PM_{10}			PM_{10}^{ASN}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ - Cattle	0.289**		0.201	0.351***		0.392**	0.069		0.128
	(0.126)		(0.133)	(0.060)		(0.060)	(0.144)		(0.150)
Δ - Pig		0.060***	0.0596***		0.002	0.0089***		0.020	0.0218
		(0.018)	(0.018)		(0.003)	(0.003)		(0.020)	(0.020)
Observations	16579	13919	13919	109202	109650	109650	3299	2790	2790
Adj R^2	0.5690	0.5656	0.5657	0.5215	0.5213	0.5217	0.5228	0.5367	0.5370
Dep. Var. Mean	15.53	15.53	15.53	30.42	30.42	30.42	10.68	10.68	10.68
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sensor-by-quadrant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: the table reports the estimates of β_a from Equation 1, where Ω is an identity matrix (absence of distance weighting). Analytical weighting assigning greater importance to sensor-day observations toward the end of each month is applied. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average planetary boundary layer height, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A1.2: Estimates Robustness - Linear Distance Weighting

	NH_3			PM_{10}			PM_{10}^{ASN}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ - Cattle	0.975***		0.824**	0.738***		0.830***	0.38		0.345
	(0.306)		(0.322)	(0.128)		(0.128)	(0.42)		(0.45)
Δ - Pig		0.062*	0.0667*		0.062*	0.0212***		0.062*	0.0290
		(0.037)	(0.037)		(0.037)	(0.037)		(0.04)	(0.04)
Observations	16579	13919	13919	109202	109650	109650	3299	2790	2790
Adj R^2	0.5768	0.5693	0.5698	0.5145	0.5143	0.5146	0.5061	0.5109	0.5113
Dep. Var. Mean	15.53	15.53	15.53	30.42	30.42	30.42	10.68	10.68	10.68
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sensor-by-quadrant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: the table reports the estimates of β_a from Equation 1, where Ω is populated using linear weights. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average planetary boundary layer height, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A1.3: Estimates Robustness - Gaussian (<50) Distance Weighting

	NH_3			PM_{10}			PM_{10}^{ASN}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ - Cattle	0.418***		0.355**	0.328***		0.380***	0.15		0.174
	(0.137)		(0.144)	(0.066)		(0.066)	(0.17)		(0.18)
Δ - Pig		0.054***	0.0552***		0.004	0.0118***		0.018	0.0188
		(0.020)	(0.020)		(0.003)	(0.004)		(0.02)	(0.02)
Observations	16579	13919	13919	109202	109650	13919	3299	2790	13919
Adj R^2	0.5767	0.5694	0.5698	0.5145	0.5143	0.5146	0.5061	0.5110	0.5114
Dep. Var. Mean	15.53	15.53	15.53	30.42	30.42	30.42	10.68	10.68	10.68
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sensor-by-quadrant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: the table reports the estimates of β_a from Equation 1, where Ω is populated using Gaussian weights, with maximum radius 50km. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average planetary boundary layer height, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

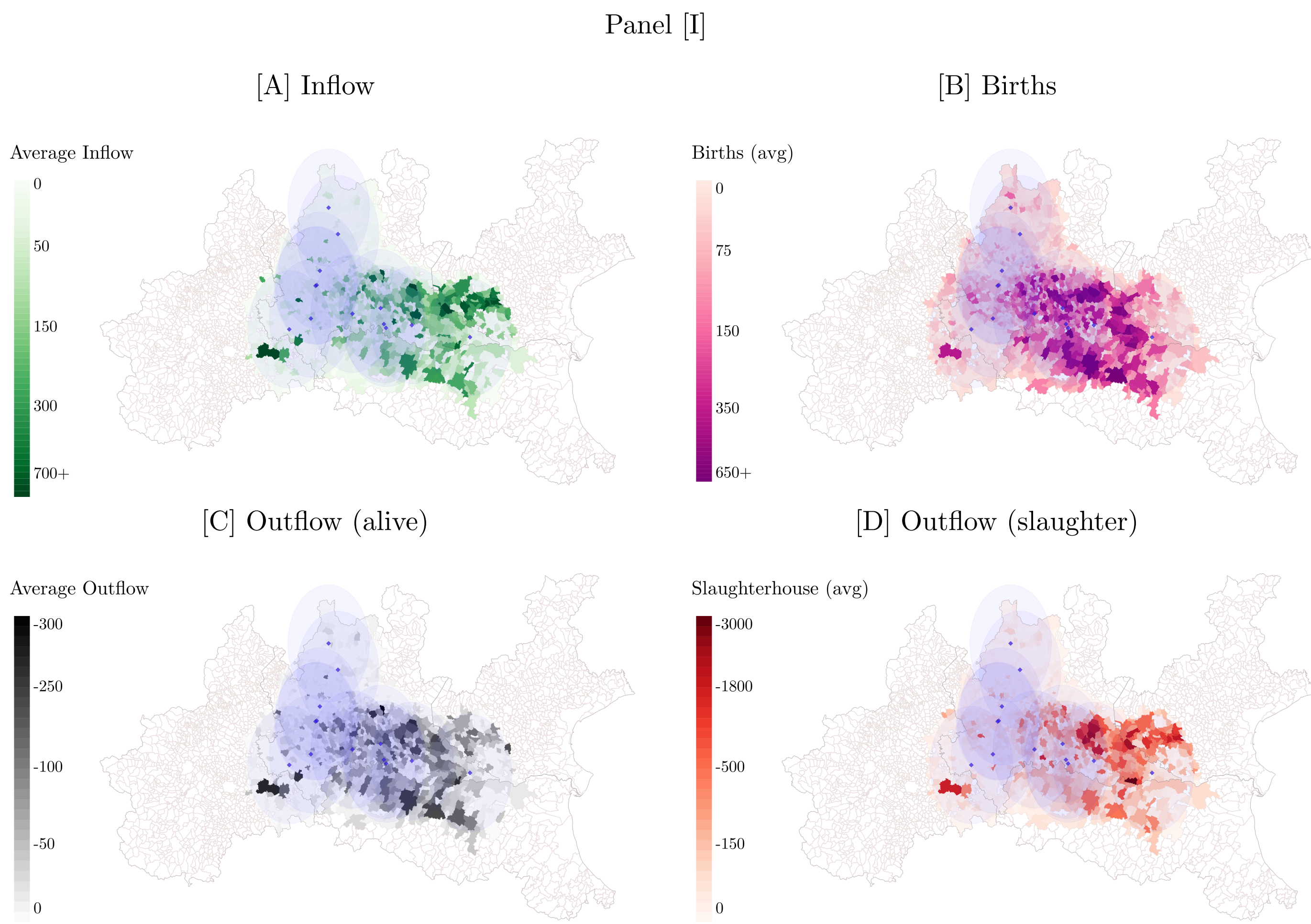
Table A1.4: Estimates Robustness - Gaussian (<60) Distance Weighting

	NH_3			PM_{10}			PM_{10}^{ASN}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ - Cattle	0.397***		0.341**	0.301***		0.350***	0.14		0.171
	(0.127)		(0.133)	(0.060)		(0.060)	(0.16)		(0.17)
Δ - Pig		0.046**	0.0464***		0.004	0.0113***		0.017	0.0180
		(0.019)	(0.019)		(0.003)	(0.003)		(0.02)	(0.02)
Observations	16579	13919	13919	109202	109650	109650	3299	2790	2790
Adj R^2	0.5767	0.5694	0.5699	0.5145	0.5143	0.5146	0.5061	0.5110	0.5114
Dep. Var. Mean	15.53	15.53	15.53	30.42	30.42	30.42	10.68	10.68	10.68
Weather Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sensor-by-quadrant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: the table reports the estimates of β_a from Equation 1, where Ω is populated using Gaussian weights, with maximum radius 60km. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average planetary boundary layer height, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

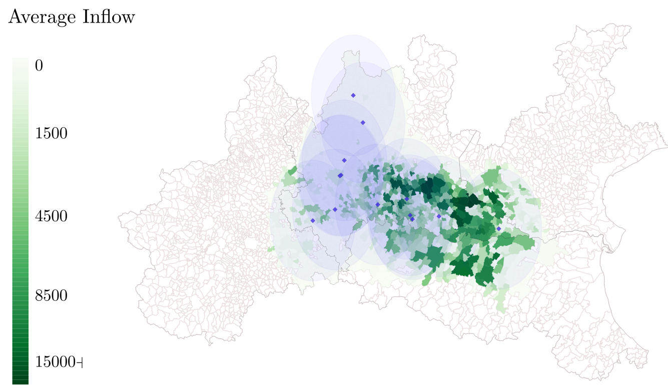
A2. Appendix Figures

Figure A.2.1: Cattle movements around stations - Sample averages (2015-2020)

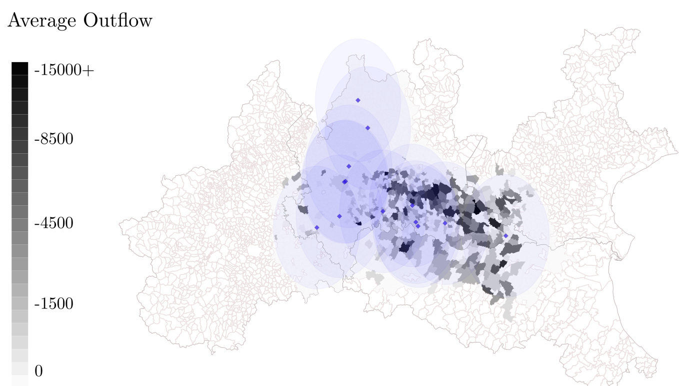


Panel [II]

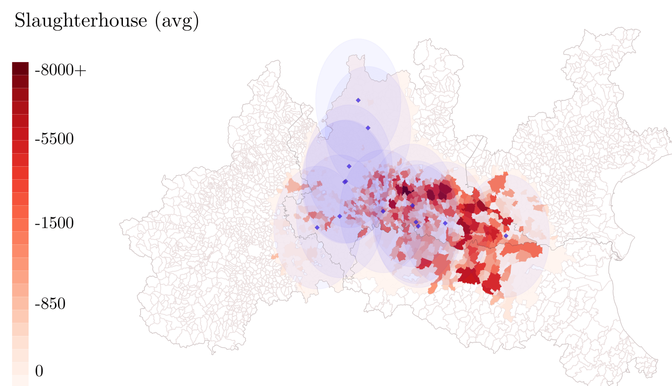
[A] Inflow



[C] Outflow (alive)

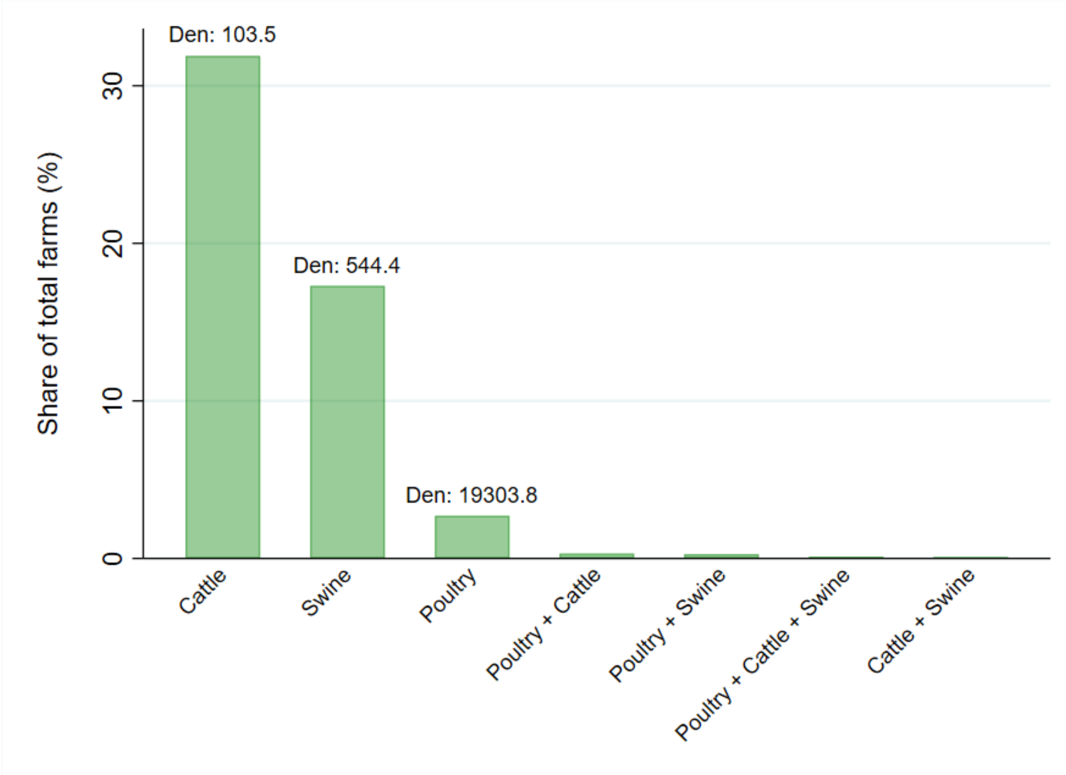


[D] Outflow (slaughter)



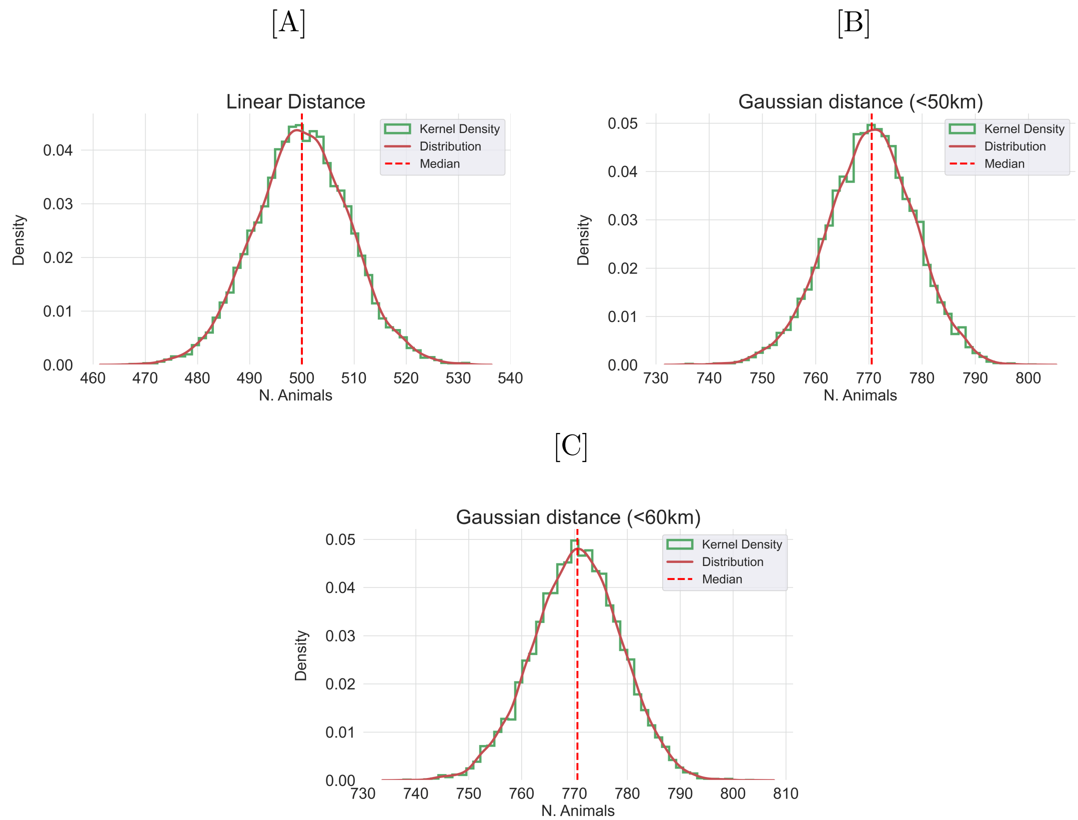
Notes: the figure plots the average monthly inflows (A), births (B), outflows (C), and slaughtered units (D) of cattle [I] and swines [II] throughout the sample period. Births data are not provided by ANZ. Animals displaced for slaughtering purposes are considered as an immediate depletion to the municipality's stock. The figure focuses on variations taking place in municipalities within a 50km radius from each stations.

Figure A.2.2: Multi-animal farming incidence



Notes: the figure reports the share of farms in the Lombardy region specializing in each combination of the most prevalent farming animals: cattle, pigs, and chicken. Source: ISTAT, 2010 Agricultural Census.

Figure A.2.3: Distributions of simulated weighted variation in livestock units (quadrant)



Notes: the figure reports the resulting distribution of a 10,000 iterations simulation of $\Delta L \times \mathbf{\Omega}$, where ΔL is a 1000-unit positive variation around a station. A unit is located at random distance $\tilde{d} \sim U(0, \bar{r})$. It is then weighted through Ω according to three different specifications: linear (A), Gaussian <50km (B), Gaussian <60km (C). The resulting headcount distribution and corresponding kernel density and median outcome are plotted.