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Exploring the impact of livestock on air quality: A deep dive into Ammonia and particulate matter in Lombardy

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ABSTRACT

The linkage between agricultural activities, particularly livestock farming, and atmospheric pollution is broadly acknowledged, and its magnitude is widely analyzed. Lombardy, one of Europe's most critical areas with regard to air pollution, has significantly large contributions from the farming industry. 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 a spatially and temporally indexed econometric model to investigate the specific impact of bovine and swine farming on the concentration levels of ammonia (NH_3) and coarse particulate matter (PM_{10}) 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 NH_3 and PM_{10} 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, we employ our findings to extrapolate the potential environmental implications of reducing livestock emissions. Our analysis suggests that bovine and swine farming could account for up to 25% of local pollution exposure, empathizing the need for targeted mitigation strategies.

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, 1 in 9 death worldwide were caused by fine particulate matter ($PM_{2.5}$) and ozone (O_3) air pollution,[1] with the former contributing to such outcome by >94% (Murray et al., 2020). By threatening human welfare through poor air quality, PM also implies a large morbidity burden on individuals: exposure to high PM levels has been associated with increased incidence of respiratory and cardiovascular diseases, such as asthma, pneumonia, hyper- tension, 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 and Carnovale, 2015; He et al., 2019). Indeed, livestock farms are a key contributor to PM emissions (Pue and Buysse, 2020). Animal husbandry operations are responsible for large releases of ammonia (NH_3), a gaseous alkaline compound that serves as a precursor in secondary particle formation, from reactions with other compounds, such as sulfur oxides (SO_x) and nitrogen oxides (NO_x), ammonia contributes to a major part of the inorganic composition of $PM_{2.5}$. This explains why air pollution from livestock farms is associated with airway obstruction diseases and severe pneumonia (Borlée et al., 2017; Kalkowska et al., 2018).

In the case of Lombardy, farming constitutes almost the only source of ammonia releases: the emission inventory of the Lombardy

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[1] Source: The Institute for Health Metrics and Evaluation (IHME) data. Available at: http://ghdx.healthdata.org/gbd-2019.

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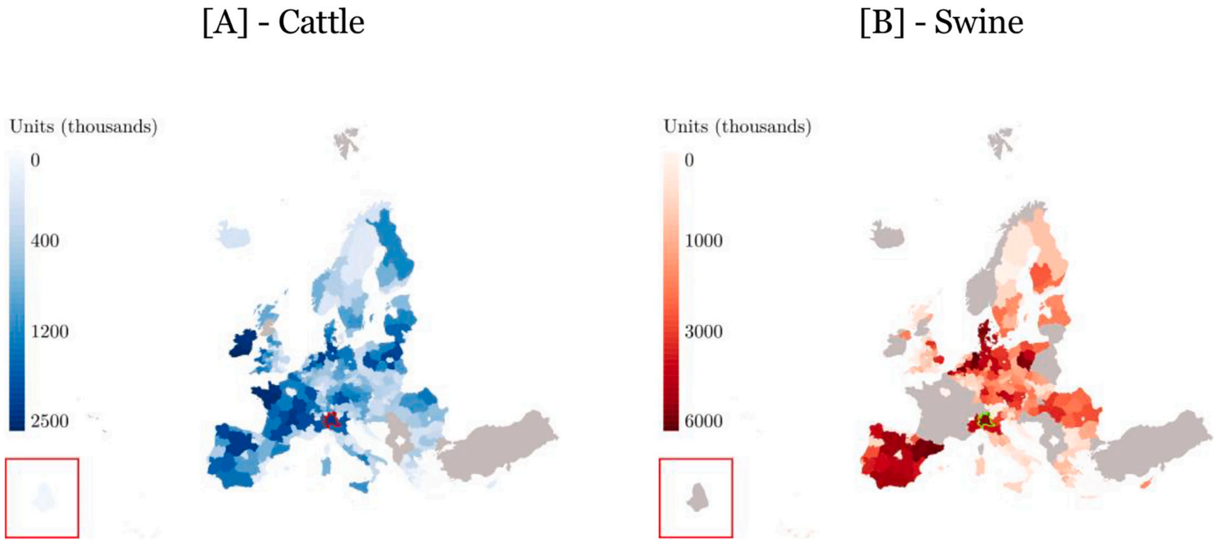


Fig. 1. Livestock presence - Eurostat NUTS2 level.
Notes: the figure reports live cattle (Panel A) and swine animals (Panel B) across European NUTS2 regions (the French Guiana region is relocated in the bottom left of the map). The Lombardy region (framed) is the 14th area in terms of absolute units 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 swine). Grey areas have no data available on livestock presence.
Source: Eurostat.

environmental agency (INEMAR, 2020) estimates that as much as 97% of all its emissions originate from farming activities in the Italian Po-valley region. Since 2005, Italy has successfully reduced NO_x and SO_2 emissions from major sources (Marco et al., 2019). NO_x and SO_2 emissions have decreased by 41% and 70% respectively, since 2005 and 2016, primarily thanks to policies tackling emissions from road traffic, residential heating, and industry (Marco et al., 2019). Conversely, ammonia decreased only by 10% and $PM_{2.5}$ emissions show positive and negative variations from 2005 to 2016 resulting in a 7% reduction between 2005 and 2016. Thus, ammonia remains a concern, as actions in the agriculture sector have been less consistent, and PM levels remain high compared to the rest of Europe, especially in Lombardy. The detrimental role of livestock in the absence of efficient air pollution control practices is well recognized in the literature (McDuffie et al., 2021). Yet, the marginal contribution of the different species of farming animals to ammonia and, in turn, PM concentrations is still poorly understood. The emission factor of a farming animal can vary considerably, depending, among others, on species, 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, which was between 0.38 and 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 looked at particulate emissions 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 and Van Heyst (2018) provide 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.

A wide variety of source apportionment techniques are available (Thunis et al., 2023) Some of these techniques employ bottom-up models that perturb source emissions (Thunis et al., 2019), while others utilize inverse modeling (Carozzi et al., 2013) or tagged trajectories (Kranenburg et al., 2013). Specifically, for PM, numerous methods rely on monitored chemical composition of particles to identify the sources contributing to the overall PM mass (Giardi et al., 2022). Here we employ a fixed-effects model with spatially and temporally indexed data that builds on exogenous high-frequency variation in wind direction and detailed data on farming animals' movements across the Lombardy region in Italy. We estimate the marginal impact of two animal kinds (cattle and swine) on ammonia and PM_{10} levels. 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 >1 million live cattle and 4 million live swine head (see Fig. 1). This, in turn, results in frequent movements of animals in and out. We take advantage of this variation 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 information 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 (the 90-degree portion of a circular area around the 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 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.

Using our estimates, we then simulate average daily levels of PM_{10} under the counterfactual stylized scenario of removing all livestock units around a sensor. We find a simulated local 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. Our study aims to quantify the average relative contribution of livestock animals to station-level recorded concentrations of pollutants rather than pinpointing 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, 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., 2019a, 2019b; Garnett, 2009). The paper contributes by establishing 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 details the empirical strategy employed. Section 3 describes the data, and Section 4 reports the main estimation results. Section 5 explores effect heterogeneity, while Section 6 presents a counterfactual calculation of pollutant concentrations and policy considerations following the evidence at hand. Finally, Section 7 concludes.

2. Methods

We calculate the incremental impact of a unit of animal, per species, on ammonia and PM_{10} levels. It's important to understand that our calculation is based on the number of animals within a fixed area. As a result, the impact can be interpreted as a variation in animal density, since the area remains constant. For this reason, we refer to 'intensity' as the quantity of animals per unit area. To estimate the marginal contribution to ammonia and PM_{10} concentrations specific to each farming animal at the aggregate level, we estimate the following regression through OLS:

$$Y_{s,t} = \beta_0 + \sum_{j \in \mathscr{B} \cap \mathscr{G}} \sum_{a \in A} \beta_a \Delta L_{a,j,t} \times \mathbf{\Omega} + \mathbf{X}'_{s,t}\mathbf{\Gamma} + \delta_{s,q} + \delta_m + \delta_y + \varepsilon_{s,t} \tag{1}$$

where Y represent the dependent variable of interest, ΔL is our main regressor, $\mathbf{\Omega}$ is a weighting matrix, $\mathbf{X}$ is a matrix of covariates with the respective coefficients ($\mathbf{\Gamma}$), and δs captures the fixed effects of our model. β_a represents the main coefficient of our study. As our study focuses on pinpointing the causal effect of livestock on pollutant concentrations,

OLS has the advantage, under our set of assumptions, to provide an unbiased and easily interpretable estimator for β.

The outcomes of interest (Y) are ammonia concentrations (NH_3), overall particulate matter (PM_{10}), and mass concentration of ammonium sulfates and nitrate (PM_{10}^{ASN}) measured daily by station s at time t. ΔL is the net sum of inflows and outflows for animal a (both within the region and from and to other regions and countries), births, and slaughters at the municipal level. The set $\mathscr{B}$ characterises a municipality j as:

$$\{ j \in \mathscr{B} : d_{i,j} < \bar{r} \}$$

hence containing municipalities within $\bar{r}$ distance from municipality i. We alternatively consider 50 km and 60 km centroid-distance as the two values of $\bar{r}$.[2] The set $\mathscr{G}$ is instead defined as:

$$\{ j \in \mathscr{G} : \angle ij_t \in WD_{i,t} \}$$

and includes all municipalities that are in the same quadrant of the direction from which wind originates as measured in municipality i at time t ($WD_{i,t}$). We use the concept of geometric angle ($\angle$) to indicate that municipalities are assigned to quadrants depending on the angle between the station and the municipality. 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. To visualize the quadrant-wind direction variation strategy implemented, we provide a graphical illustration in Fig. 2. A is instead a set of two farming animals, bovine and swine, for which monthly variation in headcount is available.

This variation in livestock units 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. By defining analytic weights as the probability of a given variation in animal headcount has realized (assuming a probability increasing linearly and monotonically), we want to impose that data points at the beginning of the month could be estimating the marginal effect captured by our β less precisely. Analytic weights are equivalent to assuming observation j belongs to a subpopulation with variance $\frac{\sigma^2}{w_j}$, where σ^2 is a common variance and w_j is the weight of the observation j.[3] 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 a weight of 1, with other observations in between weighted with a monotonic linear increment of 1/30.

[2] There exists no universal rule to assess the distance potentially traveled by pollutants, as this is closely dependent on the area's morphology, wind conditions, and the nature of airborne particles. As such, we set the boundaries of circular areas around sensors employing a data-driven approach. In Fig. A2.2 in the Appendix, we show the sensitivity of the estimated βa from Eq. (1) to gradually expanding circular areas from a radius of 10 km. For both animals and pollutants, the coefficient of interest converges to an asymptotic value between 40 km and 60 km, which leads us to exclude variations in livestock headcount taking place outside of this range. Furthermore, as the area radius increases, so does the probability of sensors relatively far from each other showing overlapping circular areas, which may induce noise in our estimates. The average intra-sensor distance is 75.4 km and 74.5 km for ammonia and PM10 sensors respectively. Hence, we deem the 60 *km* threshold to be an adequate upper bound to consider variation in livestock units relevant to a given sensor.

[3] Weights are implemented in Stata. For further, refer to Stata Technical Bulletin, issue 20, July 1994.

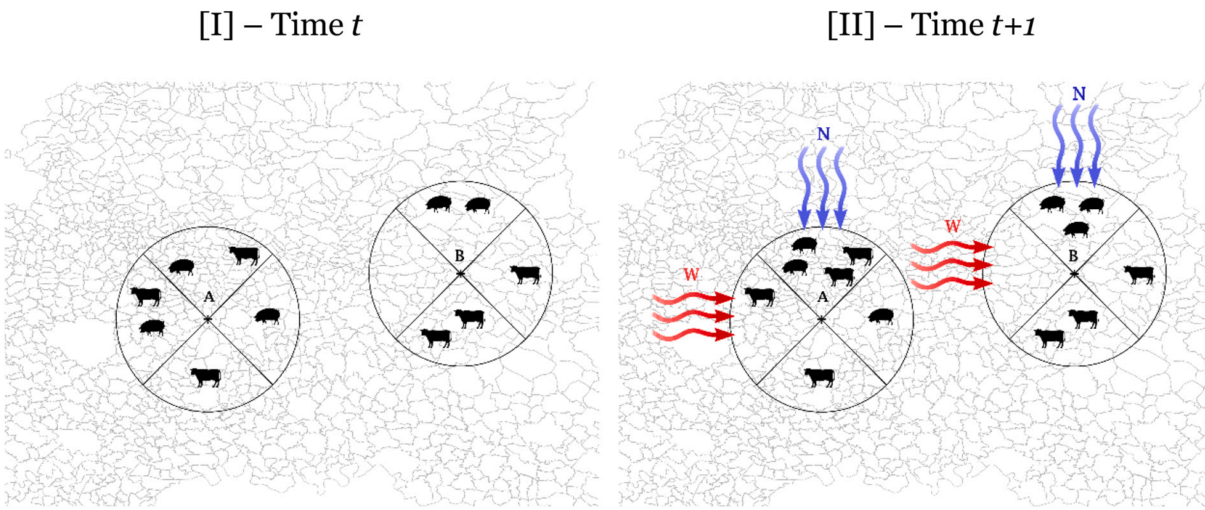


Fig. 2. Station quadrants and wind direction.

Notes: the figure provides an example of quadrant-specific variation conditional on wind direction. Consider the stations A and B at time t (Panel I). The existing stock of swine and cattle within r kilometers from the sensor is divided across four quadrants, i.e., 90-degree portions oriented along main cardinal directions (North, East, South, West). Consider the variation in animal headcount from time t in time $t+1$. In our specification, this variation is expected to influence concentrations of pollutants only as long as it takes place upwind from the sensor. For instance, on days when West wind is blowing (red arrows), station A will be imputed a reduction in swine stock, while station B will exhibit no change in animal presence around the station. Conversely, on days of North wind, station A will be imputed a positive change in the stock of both swine and cattle, while in station B the increase will be observed only in swine headcount. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$\boldsymbol{\Omega}$ is a diagonal matrix of weights based on the distance between sensors and 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, $\boldsymbol{\Omega}$ partially discounts the variation happening further away from each station. Considering a total of M municipalities around a given sensor, in our baseline specification, $\boldsymbol{\Omega}$ is an identity matrix of size $M \times M$ (i.e., no discounting based on distance implied). We then test the robustness of our results by populating $\boldsymbol{\Omega}$ with linear and Gaussian distance weights.[4] To better understand how we compute variation in livestock units under different weighting schemes, a numerical example is reported in the Appendix (Section A3.1).

$\mathbf{X}$ 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, and $\boldsymbol{\Gamma}$ is a matrix of coefficients. $\delta_{s,q}$, δ_m, and δ_y represent a set of sensor-by-quadrant, month, and year-fixed effects.[5] Sensor-by-quadrant allows for different time-invariant intrinsic characteristics not only across sensors, but also around a sensor and, as such, it is deemed as the most conservative approach.[6] Our model estimates 66 weather control parameters and 62 fixed effects parameters overall, in addition to our coefficients of interest. Finally, $\varepsilon_{s,t}$ is an error term, assumed to be normally distributed. We allow for variance in error to be dependent on our regressors, estimating heteroskedasticity-robust standard errors.[7]

The marginal effect of a livestock unit for animal a is captured by our main coefficient of interest, β_a. To be able to identify, 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 in our estimates. Despite the absence, in the current regulatory framework of Lombardy, of policies aimed to curb 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. Indeed, in our specification, it is enough to assume non-adapting behavior from farmers to wind flows, i.e., animal stock decisions being independent of observed and expected wind flows. In addition, the presence of station-, quadrant-, and time-fixed effects allows differentiating part of the confounding variation that may be related to more

[4] Linear weights are computed as in Eq. (2):

$$w_{ij} = 1 - \frac{d_{ij}}{\overline{r}} \tag{2}$$

while Gaussian weights obey to Eq. (3):

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

[5] The use of lags and interactions, as well as the choice of fixed effects, follows the strategy adopted by Deryugina et al. (2019). The results are robust to less conservative structure of weather covariates, excluding lags and interaction terms.

[6] The results are mostly unchanged when only sensor fixed effects are included in the regression.

[7] The choice of heteroskedasticity-robust standard errors is motivated by our model using a relatively small number of sensors and a large number of temporal observations (days), hence likely inducing serial correlation in the error. We refrain from clustering standard errors at the sensor level given the limited number of clusters available, especially with regards to ammonia stations (Cameron and Miller, 2015: Abadie et al., 2023). To assess the presence of residual correlation in the model, we plot model residuals against the fitted values in Fig. A2.3.

polluted areas with relatively more frequent animal displacement.[8]

Conditional on observables and fixed effects, we also argue against the likelihood ofour 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 pollutant contribution, the absence of data available on the movements of other animals, particularly poultry, may be especially concerning, being this the third major specie in terms of air pollutants contribution.[9] This would be particularly concerning under the hypothesis that 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 Fig. A2.4 that the share farms specializing in more than one animal are relatively small. Farms whose production includes at least two out of three species (cattle, chickens, and swine) are $<$1% of all breeders, with the share of farms breeding all three animals being $<$0.2%. This is partially confirmed by observing that variation in the number of cattle and swine units at the municipal level does not correlate.[10] Moreover, poultry farming appears to be more concentrated, with a relative density of $>$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 significantly reduces the concern of omitted variable bias, reinforcing our assumption. Finally, our model implies linearity in the effect of livestock change. This assumption simplifies the intricate process of PM formation through secondary aerosol via chemical 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

A flowchart describing the data used in this paper can be found in Fig. 3. We access publicly available daily data on NH_3 and PM_{10} concentration levels and weather conditions in the Lombardy region from ARPA Lombardia.[11] We focus on the years between 2015 and 2020 to match the frequency of livestock data. Some stations have been active for a short amount of time during those years (as the measurement activity ceased or started at the extremes of our sample period).[12] As such, we restrict the sample to stations for which daily concentration data is available for at least 365 days between 2015 and 2020, obtaining 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). We obtain a final dataset of 16,577 day-station-wind direction observations for NH_3, 109,663 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 daily 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[13] and compute average daily values. Each of these variables directly impacts airborne pollutant concentrations. Warmer temperatures are usually associated with lower concentrations, given higher thermal dispersion. Positively correlated with temperature, PBLH constitutes an even more cogent measure for vertical dispersion: higher PBL implies increased dispersion capacity and is associated with lower pollutant concentrations (Seidel et al., 2010). 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 PM_{10} 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 Fig. 4. 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, 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 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 in the region’s central plains, but South-East and South-West areas experience a higher probability of winds flowing respectively from the North and the East. Despite some patterns, considerable variability at the station level is observed. This is particularly relevant for our strategy: observing wind consistently blowing from the same direction throughout the month would imply that our fixed effects structure, which controls both for month and sensor-by-quadrant time-invariant characteristics, would absorb most of the effect of the change in livestock units. In this case, our coefficients of interest would capture noisy residual variation. Significant variation in wind direction, both within the same sensor and across sensors, mitigates this concern. 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.

Data on livestock presence and movements are available through the

[8] To this aim, it is also important how, with specific reference to ammonia, $>$95% of total emissions are ascribable to livestock. This importantly reduces the concern of unobservables spatially correlated with sensor proximity (e.g. other agricultural activities) inducing bias in the estimates. PM concentrations are more susceptible to confounding emission sources, which, however, are less likely to be spatially correlated with proximity to a measuring station, such as traffic or industrial activities.

[9] 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.

[10] Pearson’s product-moment correlation coefficient: 0.02

[11] ARPA: Regional Agency for Environmental Protection. The agency collects hourly data on NH_3 and PM_{10} concentrations but disseminates the information as daily averages.

[12] For NH_3 sensors, only two stations are not active throughout the entire period (Cremona Borghi, inactive since January 2017, and Piadena, inactive between March 2014 and June 2016). For PM_{10}, 11 stations cease measurement only between 2017 and 2018.

[13] The measure is provided at $0.25^{\circ} \times 0.25^{\circ}$ grid level.

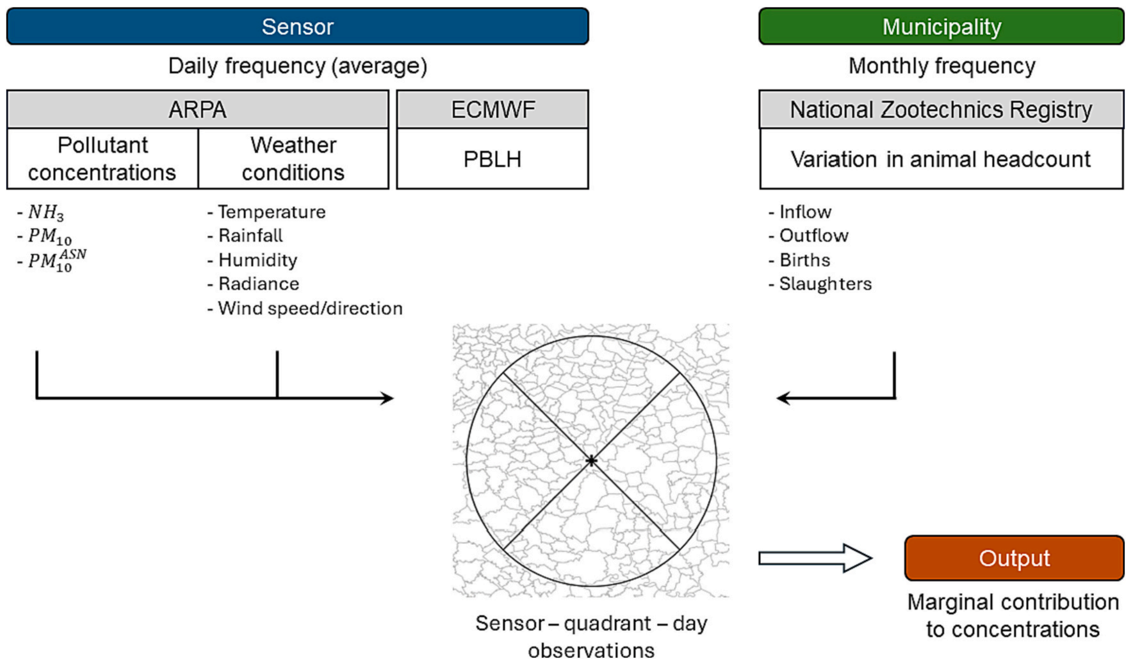


Fig. 3. Data sources - flowchart.
Notes: the figure plots a flowchart of the data used in our study, specifying the geographic and temporal level of the information available and the corresponding sources.

Table 1
Descriptive statistics - pollutants and weather.

	Overall	Within	Between
Panel A - Pollutants			
NH_3	15.74		
($\mu g/m^3$)	(19.97)	(14.06)	(12.84)
	[0.0; 430.6]	[−29.1; 429.2]	[3.0; 45.4]
PM_{10}	30.61		
($\mu g/m^3$)	(20.70)	(19.99)	(5.15)
	[0.0; 264.0]	[−10.0; 264.4]	[13.0; 41.6]
PM_{10} (AS + AN)*	10.95		
($\mu g/m^3$)	(10.78)	(10.77)	(0.57)
	[0.0; 58.3]	[0.0; 58.7]	[10.5; 11.7]
Panel B - Weather			
Temperature	13.87		
($^\circ$ 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	1654.82		
(m)	(1415.71)	(1412.01)	(100.24)
	[11.4; 5553.5]	[−127.5; 5543.8]	[1439.3; 1803.9]

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 the sensor and the overall mean. Parentheses include standard deviations. Brackets report minimum and maximum values. Within and between statistics are computed through the command xtsum in Stata.
Source: ARPA Lombardia, ECMWF.

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, cattle and swine.[14] 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.[15] 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 compute the stock of animals registered in each municipality, 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 surrounding Lombardy's sensors exhibit the high prevalence of livestock animals typical of the Lombardy region, with an average of >1000 cattle units and 2500 swine units per municipality. Both cattle and swine numbers appear to be decreasing, although the variation is still a relatively small share of the existing stock (Table 2). Fig. 5 shows instead how the majority of animal husbandry activities are

[14] Cattle identifies all bovine farming species, including Italian Mediterranean buffalos. Data on swine is only available starting in 2016.

[15] 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.

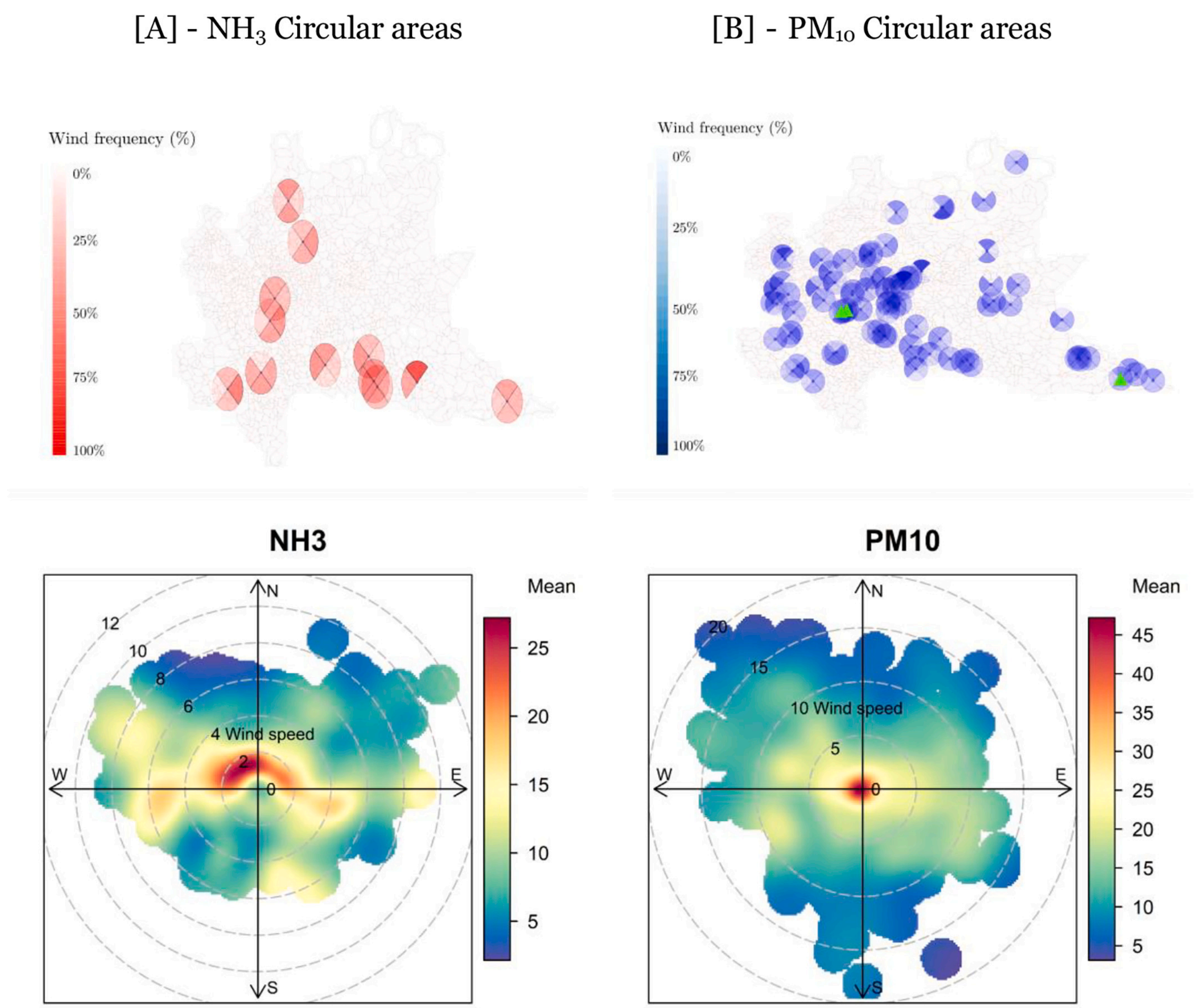


Fig. 4. Frequency of wind directions - regional and sensor values.

Notes: the figure reports quadrant-specific wind frequency at the station level, calculated as the number of days recording wind flowing from a given quadrant over the entire sample period (2015–2020). Triangles mark sensors that provide decomposed data on ammonium nitrates and ammonium sulfates. Panel A plots wind frequencies for ammonia stations, while Panel B plots the same statistics for PM_{10} stations. Polar plots are reported at the bottom to visualize the mean concentrations of each pollutant of each combination of wind direction and speed at the regional level. These plots are obtained using the function polarPlot in R. Computational details for calculating the concentration surface can be found in Carslaw et al. (2006) and Westmoreland et al. (2007).

concentrated in the South-East area of the Po Valley, both in terms of cattle and swine breeding. This is reflected both in average monthly outflows and inflows, which tend to be larger in numbers in areas more populated by farming animals (Fig. A2.1) and in consistently higher concentrations of ammonia located within areas of high livestock density (Fig. 6, 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.

4. Results

The results of estimating Eq. (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 the estimates of βa, respectively, when including only the variation in cattle units and swine units. The third column includes the two variations as separate variables and estimates the marginal contributions when the two regressors are included together. In Panel B, we instead present standardized coefficients of the same estimated relationship. We center the

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)	(1429.43)	(1348.00)	(565.28)
	[0.0; 1663.0]	[−37.0; 1641.0]	[0.8; 50.9]	[0.0; 23,932.0]	[−967.8; 23,342.1]	[1.9; 1424.5]
Births**	43.39			–		
(monthly)	(88.57)	(80.46)	(42.84)	–	–	–
	[0.0; 1379.0]	[−74.4; 1362.2]	[8.9; 117.8]	–	–	–
Outflow	−6.61			−450.06		
(monthly)	(30.35)	(29.91)	(6.02)	(1650.23)	(1583.29)	(547.31)
	[−1201.0; 0.0]	[−1197.3; 10.2]	[−16.8; −0.5]	[−20,431.0; 0.0]	[−19,957.8; 994.5]	[−1444.6; −0.7]
Slaughters	−57.16			−370.86		
(monthly)	(190.71)	(179.90)	(74.50)	(1044.20)	(980.95)	(412.65)
	[−3643.0; 0.0]	[−3511.9; 137.0]	[−194.2; −5.2]	[−14,064.0; 0.0]	[−13,575.4; 631.7]	[−1002.6; −1.5]
Net variation	−262.63			−415.14		
(monthly)	(4719.15)	(3977.39)	(3035.25)	(433.52)	(263.28)	(384.11)
	[−20,706.0; 9072.0]	[−16,007.1; 13,482.5]	[−7324.1; 2386.3]	[−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)
	[2204.25; 497,245]	[−170,965.74; 351,963]	[13,925.67; 326,303]	[0.00; 1,642,738]	[−552,364.85; 1,448,462]	[1117.73; 873,293]
Tot animals	1088			2533		
(municipality)	(2382)	(197)	(2318)	(7655)	(1102)	(7189)
	[1.00; 35,915]	[−5255.98; 4957]	[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 the sensor and the overall mean. Parentheses include standard deviations. Brackets report minimum and maximum values.
Source: National Zootechnics Registry.
* 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.

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 looking at concentrations of ammonia, all coefficients are significant, at least at a 5% level across different specifications. The inclusion of variations in both species in the equation has only a minor impact on the respective 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). On the one hand, 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. On the other hand, similarity in the coefficients shows how positive variation in livestock units induces a comparable increase in NH_3 and PM_{10} concentrations and, as such, supports the belief that PM mass concentrations observed when livestock increases are indeed the result of secondary aerosol formation through ammonia.

While we would expect the observed increase in PM_{10} to be attributable to ammonium nitrates and ammonium sulfates particles spurring from ammonia gaseous emissions, the relatively different and not significant coefficients observed in Columns 7 to 9 can be explained by data on 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 pollutant concentrations occurring toward the end of the month, where the shift in the animal count is more likely to be 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 pollutant measurement than those located in close proximity to it, we apply different specifications of $\mathbf{\Omega}$, i.e. varying the distance discounting weights to the variation in livestock units. In this case, coefficients are not directly comparable to the ones obtained before, as the weighting implies a rescaling of our main regressor (ΔL) and, in other words, inevitably inflates the magnitude of $\widehat{\beta}_a$ by magnifying the relevance of a one-unit increase. To compare our estimates, we iteratively simulate a 1000-unit increase in a quadrant and use the derived values

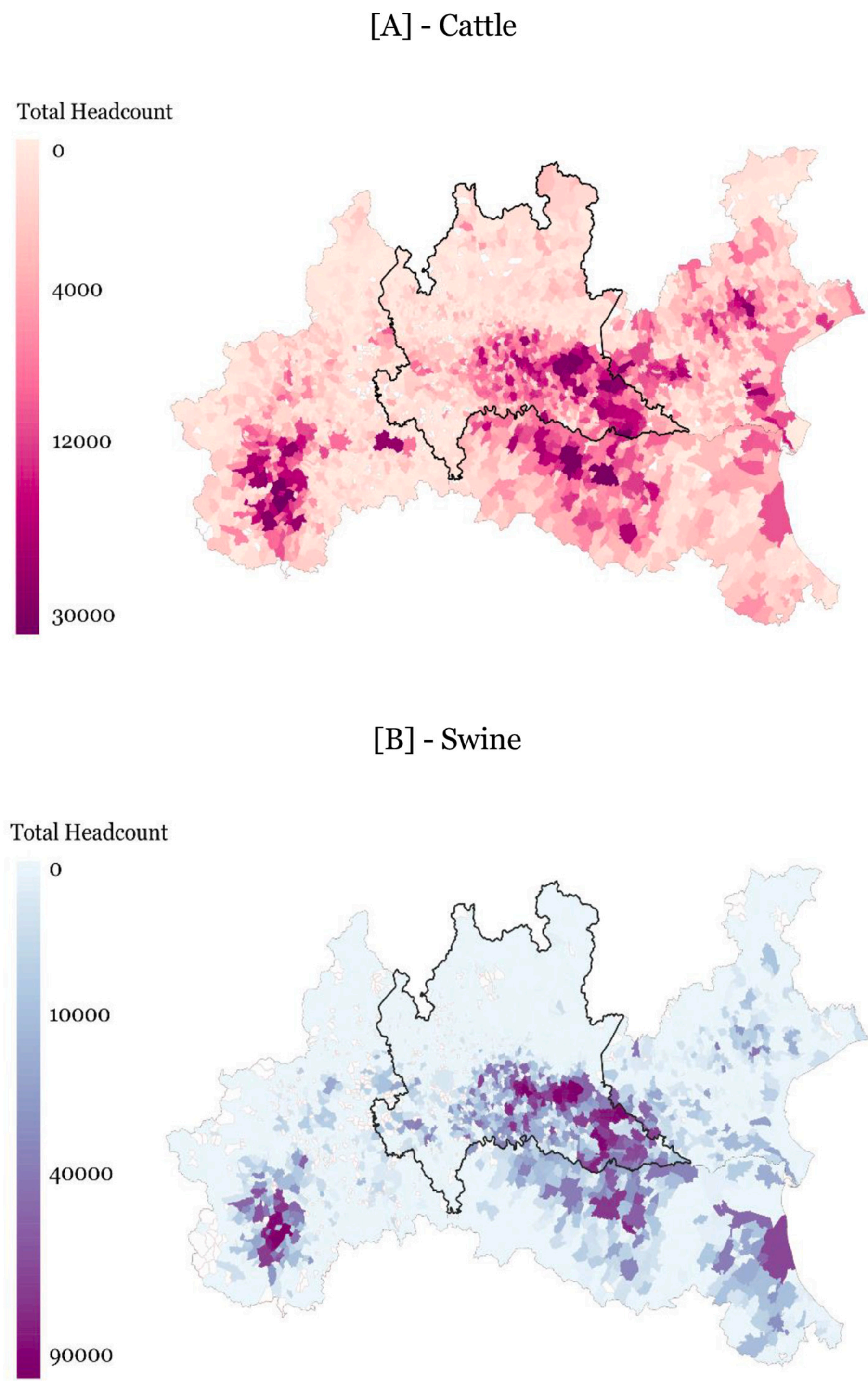


Fig. 5. Animals total headcount.
Notes: the figure reports the time average total headcount of cattle (Panel A) and swine (Panel B) at the municipal level across four regions: Lombardy (borders in bold), Piedmont, Emilia-Romagna, and Veneto. The region's area covers all municipalities located within a 60 km radius of at least one NH3 or PM station.

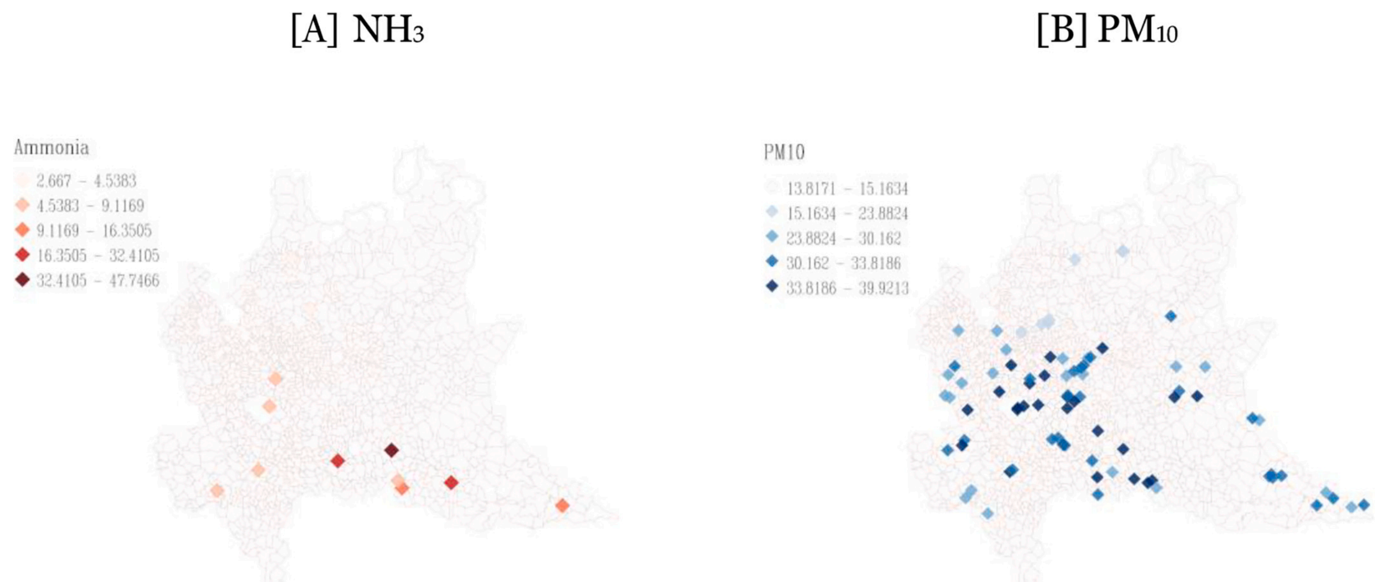


Fig. 6. Pollutants concentration - sensor sample average.
Notes: the figure plots ammonia (Panel A) and PM stations in Lombardy. Sensor color is determined by average daily concentration ($\mu g/m^3$) throughout the year at the sensor level. Max - Min values: [2.7; 47.7] Panel A; [13.8; 39.9] Panel B.

of $\Delta L \times \mathbf{\Omega}$ in the given quadrant to rescale the estimated coefficients.[16] We summarize the results in Fig. 7.[17] 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 $\mathbf{\Omega}$ lead to comparable results. The marginal effect of 1000 cattle units oscillates between 0.22 and 0.33 $\mu g/m^3$ of NH_3 and 0.27 and 0.41 $\mu g/m^3$ of PM_{10}. The same variation in terms of swine units provides estimates fluctuating between around 0.02 and 0.05 $\mu g/m^3$ of NH_3 and 0.004 and 0.16 $\mu g/m^3$ of PM_{10}.

To get a better understanding of our results, we need to stress how the impact on concentrations is fundamentally different from that on emissions, which causes our results to be inherently separate from emission factors more commonly found in the literature.[18] Concentrations are influenced by the specific geographical, meteorological, and chemical conditions of the region where the emissions occur. This is why we can only draw a partial analogy between our estimated impact on ammonia concentrations and the ammonia emission factors from the regional emission inventory (INEMAR, 2020), which would otherwise constitute a natural benchmark, at least in terms of geographic region. Comparing these, we observe a similar order of magnitude difference between cattle and swine emission factors as the one identified in our estimates, with cows showing emissions one order of magnitude higher. We cannot, however, make the same comparison with PM_{10} concentrations and the corresponding emission factors. In fact, the latter pertain to direct emissions, whereas our estimates also include secondary PM_{10} concentrations.

There, our 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 Eq. (1), letting the marginal impact of farming animal variation vary through the source quadrant. Analytically, Eq. (1) is expanded as follows:

$$Y_{s,t} = \beta_0 + \sum_{j\in\mathscr{B}\cap\mathscr{G}}\sum_{a\in A}\beta_a \Delta L_{a,j,t} + \sum_{j\in\mathscr{B}\cap\mathscr{G}}\sum_{a\in A}\sum_{q\in\mathscr{Q}}\eta_a \Delta L_{a,j,t}\times D_q + \mathbf{X}'_{s,t}\mathbf{\Gamma} + \delta_{s,q} + \delta_m + \delta_y + \varepsilon_{s,t} \tag{4}$$

where, for simplicity, we consider the absence of weighting ($\mathbf{\Omega}$=I), and D_q is an indicator assuming value 1 when variation originates from quadrant $q \in \mathscr{Q}$ (the set including the four quadrants), zero otherwise. Note that our fixed effects structure naturally absorbs the differential intercept for each quadrant. The results are presented graphically in Fig. 8. We take as reference group livestock headcount variation

[16] To clarify this aspect implied by our weighting strategy further, assume a 1000-units positive variation taking place around a station. Livestock units are located at a random distance $\widetilde{d}$ from the sensor, where $\widetilde{d}$ is drawn form a uniform distribution $\widetilde{d} \sim U(0, \overline{r})$. Each unit is then assigned a distance-based weight according to our different weighting strategies. It is then computed the corresponding ΔL (refer to the numerical example in Section A3.1). By randomly simulating the distance of each unit, we are actively randomizing the weight received by each unit. This, in turn, implies a different computed value of $\Delta L \times \mathbf{\Omega}$ depending on the outcome of the randomization. To show it, we iteratively simulate (10,000 iterations) a 1000-units positive variation around a station and apply the corresponding weighting to each unit. We then plot the corresponding value of $\Delta L \times \mathbf{\Omega}$ in Fig. A2.5.

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

[18] For instance, Hristov et al. (2011) find an average ammonia emission factor 59 g per cow per day. Philippe et al. (2011) provide a summary of swine emission factors under different waste management systems, between 0.38 and 27.2 g/day. However, it is not straightforward to determine how this would translate into ammonia concentrations at aggregate level in the context of their studies.

Table 3
Baseline estimates.

	NH$_3$			PM$_{10}$			PM10ASN		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A] - Δ10^3-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 - Swine		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 - Swine		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	16,579	13,919	13,919	109,202	109,650	109,650	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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sensor-by-quadrant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

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

happening in Southern quadrants. The results highlight how movements in farming animals tend to have a larger impact on pollutant concentrations at the sensor level when they occur to the North of a station. This finding appears in line with the evidence presented in Fig. 4: North winds are usually associated with lower levels of pollutants, which reduces the extent of confounding variation, particularly with respect to particulate matter, and makes fluctuations in the livestock units more crucial in driving up and down the concentrations of airborne pollutants. The effect appears instead to be homogeneous across other quadrants, with smaller and primarily non-significant coefficients associated with the interaction terms.

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 concentrations measured on a relatively smaller network of stations. The presence of one or few sensors driving the results may cast doubt over the accuracy and generalizability of our results. To this aim, we iteratively repeat the estimation, dropping one sensor at each iteration. The new coefficients obtained for ammonia through this methodology are plotted in Fig. 9. 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 $\bar{r}$ radius circular area. 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 offers 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.[19] 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 closely monitor concentrations in the farming area.[20] 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.[21] 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, dropping a single sensor has a more marginal impact on the overall sample. Hence, to assess the presence of sensors in critical areas driving the results, we repeat the above procedure but drop all stations in a province (Fig. 10).[22] 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. The 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 the area surrounding a station. Using data from ISTAT,[23] we calculate the resident population within a 50 km radius of the station and couple it with information on the number of livestock units within each circular area. We then simulate a hypothetical

[19] The sensor is located within 100 m from the breeding facility. The exact location of the farm is excluded for data privacy.

[20] The sensor is located between two facilities placed within 1 and 1.5 km. The exact location of the farms is excluded for data privacy.

[21] 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.

[22] The Lombardy region is divided into 12 provinces. In brackets, the number of PM10 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).

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

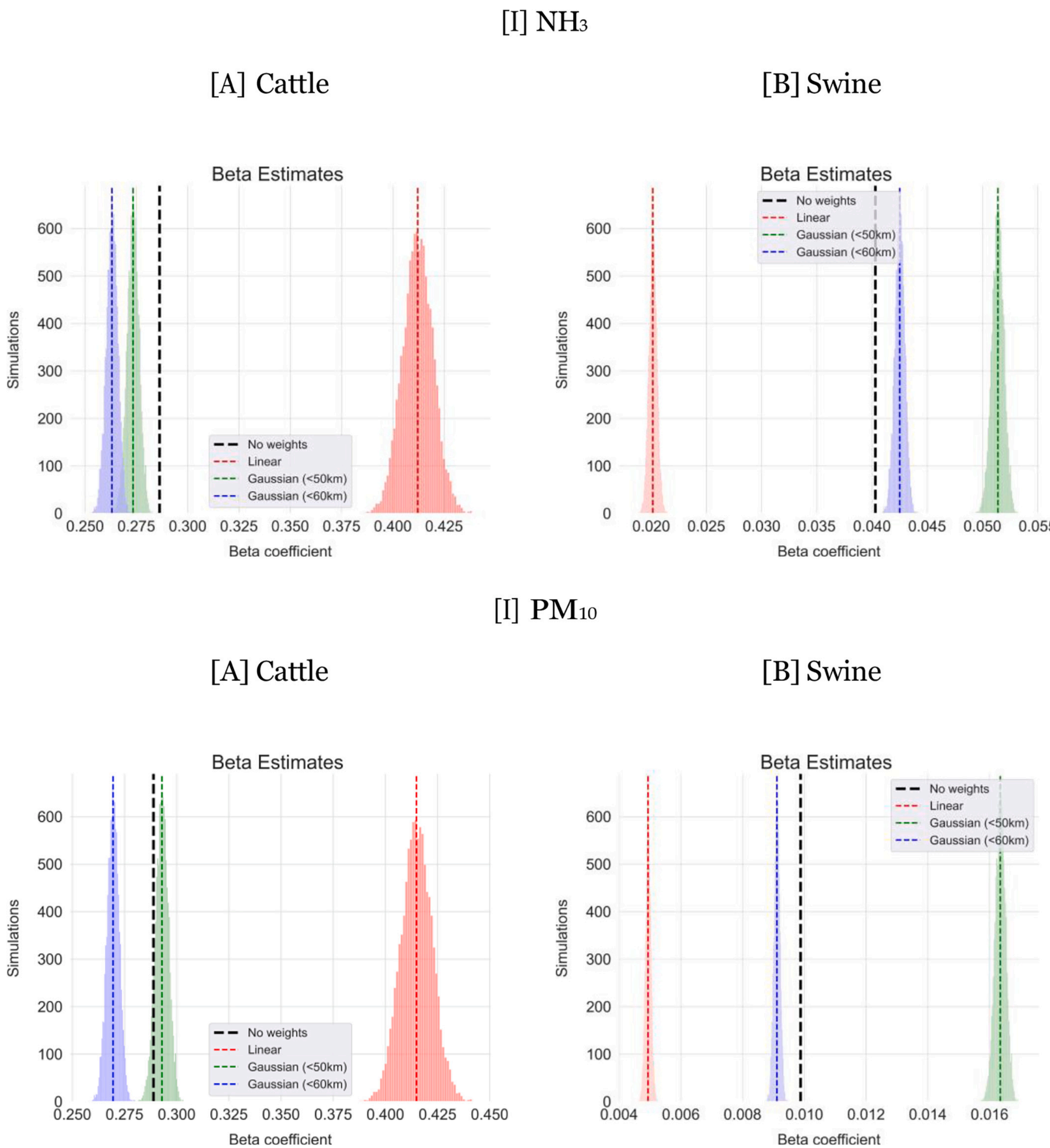


Fig. 7. Distributions of simulated weighted variation in livestock units (quadrant).
Notes: the figure compares the marginal contribution of a 1000-unit positive variation estimated without distance discounting weighting with that obtained through different specifications of **Ω**. Estimates are presented separately by pollutant (Panels I and II) and farming animal (Panels A and B). Coefficients are estimated according to Eq. (1), while **Ω** weights are computed according to Eqs. (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-unit variation distribution.

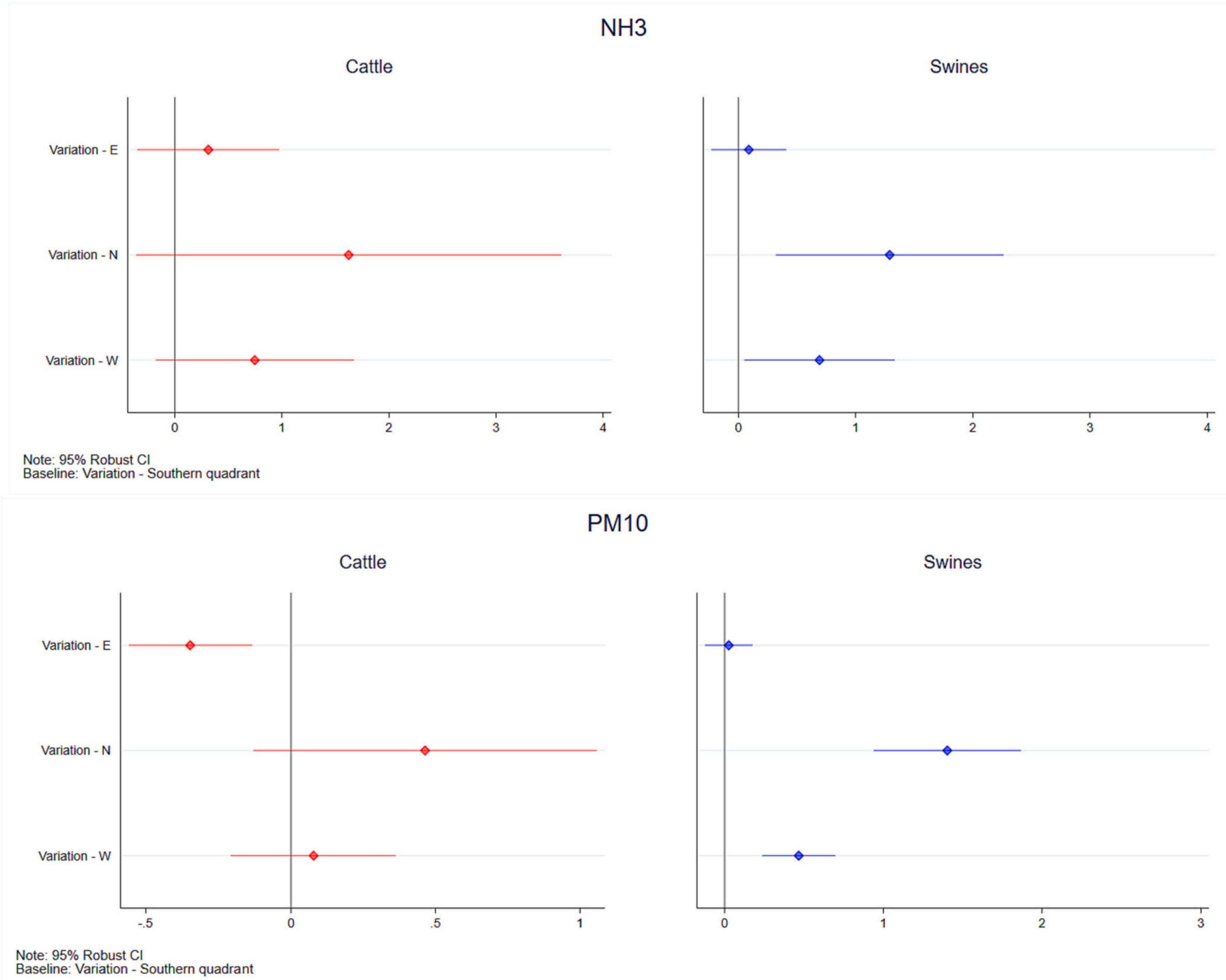


Fig. 8. Effect heterogeneity - Wind direction.
Notes: The table reports the estimates of η_a coefficients from Eq. (4). The control group is the variation in livestock units taking place in the quadrant South of each sensor. Weather controls (temperature, wind direction, wind speed, rainfall, radiance, humidity, average PBLH, interacted with each other up to three lags) and month, year, and station-by-quadrant fixed effects are included. Robust confidence intervals at 95% are plotted.

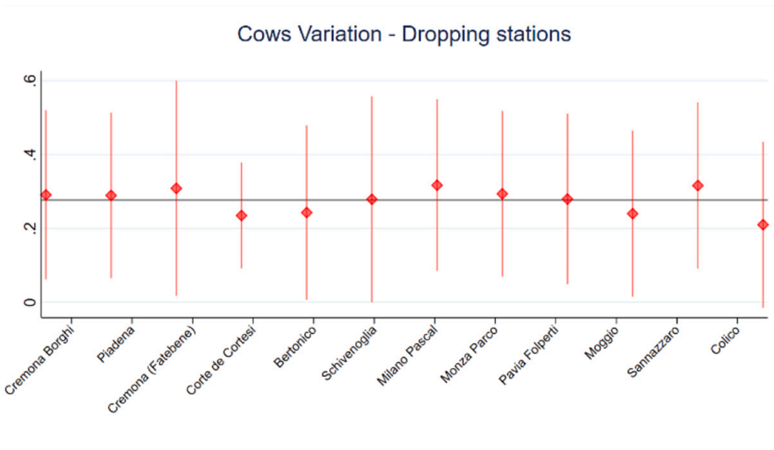
scenario where we remove all farming animals from each circular area, *all else equal* (i.e., keeping all other observable and unobservable factors constant, including weather conditions), leveraging the coefficients we obtained from a 1000-unit variation analysis to estimate the corresponding reduction in concentrations of air pollutants.[24][25] This exercise does not aim to explore a viable policy action to improve air quality in the region (i.e., the complete dismantlement of the farming industry) but rather to provide an estimate of the contribution of livestock to daily pollutant concentrations. Given the linearity of our approach, the expected results of a less sizeable reduction in livestock units can be easily inferred from our analysis. Moreover, provided 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 PM_{10} concentrations.

Panel A in Fig. 11 shows the results of this exercise by plotting the reduction in daily PM_{10} 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 PM_{10} 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 <30 μg/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

[24] 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.

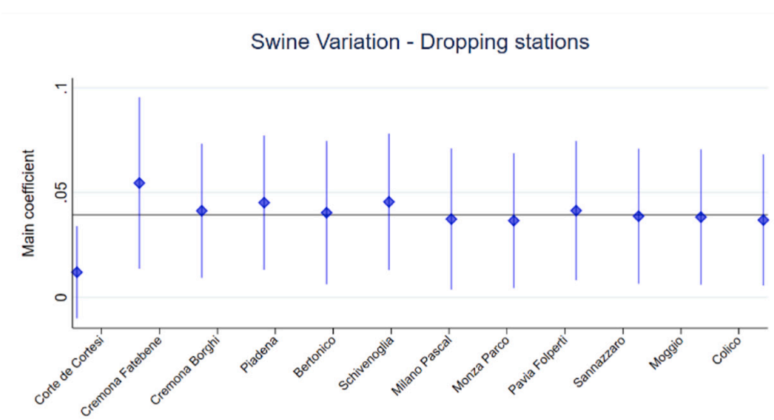
[25] Population and livestock headcount data are available at the municipality level. To avoid double- counting, whenever a municipality lies within a 50 km radius of multiple stations, its population is imputed to different circular areas in equal shares. The potential noise in the calculations induced 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.

[A] – Cattle



Station	*Cattle (Area 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

[B] – Swine



Station	*Swine (Area 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

Fig. 9. Effect heterogeneity - Dropping NH_3 stations.
Notes: The figure plots the estimates of β_a from Eq. (1), with $\mathbf{\Omega} = \mathrm{I}$, 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 circular area is reported.

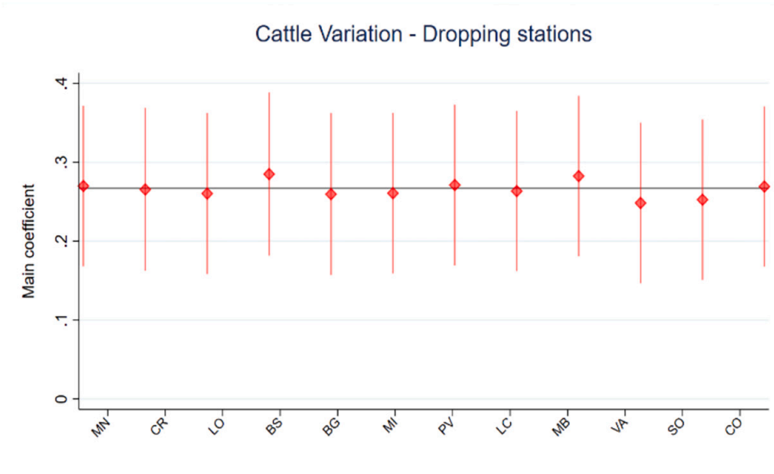
manufacturing. However, this also means that less urbanized areas are disproportionately burdened by the presence of livestock and are unable to fully benefit from high air quality.

Second, looking at Panel B, the areas touched more heavily by air pollution from livestock sources, despite lower urbanization, display considerably high population density: nearly 7 out of 14 million people reside within 50 km of those stations that would benefit from a counterfactual level of PM_{10} concentrations below 30 $\mu g/m^3$ in our simulation. Furthermore, circular areas around stations that would experience the highest percentage reduction (>20%, peaking at roughly 25%) appear surrounded by almost 2 million inhabitants.[26] 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

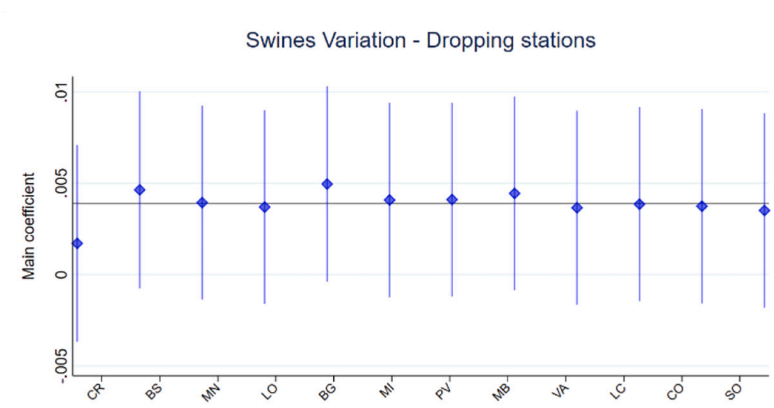
[26] In this calculation, we do not factor in individuals residing outside the 60 km circular areas used to obtain our estimates, as this would require a more comprehensive analysis of how pollutants are transported across the region, which is beyond the scope of this paper.

[A] – Cattle



Station	*Cattle (Area 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

[B] – Swine



Station	*Swine (Area 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

Fig. 10. Effect heterogeneity - Dropping PM_{10} stations.
Notes: The figure plots the estimates of β_a from Eq. (1), with $\mathbf{\Omega} = \mathrm{I}$, where observations in the province 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 circular area is reported.

sector, particularly in densely populated regions with high livestock density, like Lombardy, where the secondary formation of ammonium nitrates often reaches >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 and PM_{10} in the Lombardy region. We used daily observations from 12 ammonia monitoring stations and 75 PM_{10} 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 PM_{10} 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

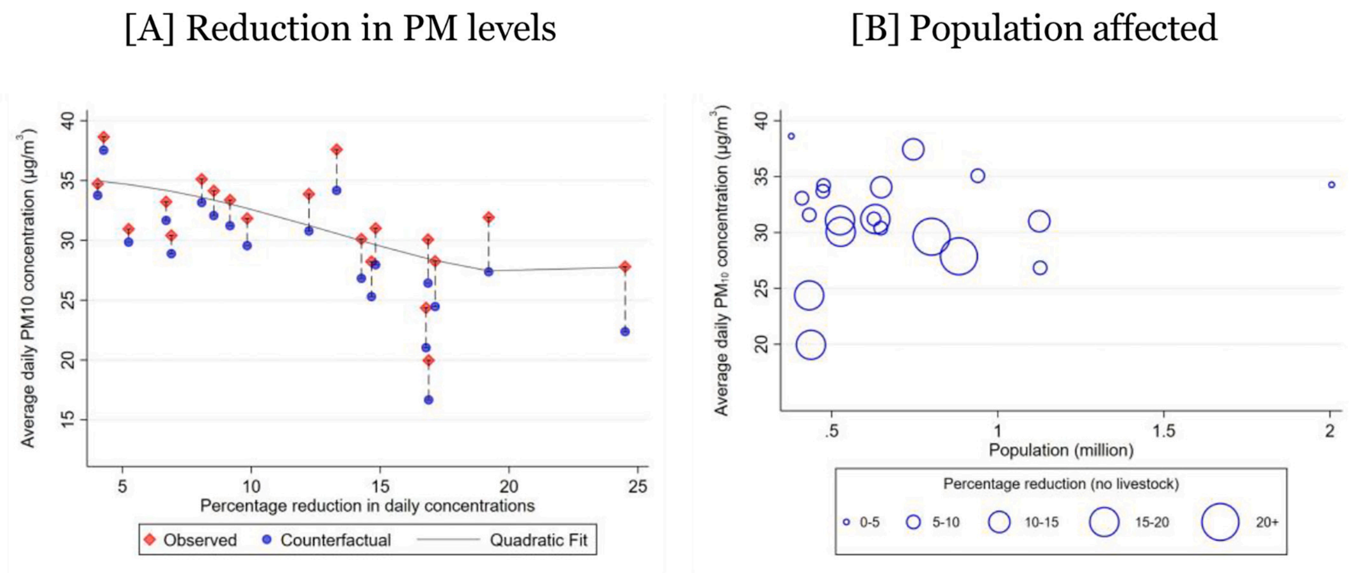


Fig. 11. Counterfactual PM levels and population exposure.
Notes: the figure shows the counterfactual scenario simulating the absence of bovine and swine livestock units. For visual purposes, sensors are grouped into twenty bins, calculated conditioning on yearly average concentrations. Panel A shows the relationship between average daily concentration and the corresponding percentage daily average reduction in each bin in the absence of swine and cattle. Panel B relates reduction under the counterfactual scenario with the population residing within a 50 km radius of a station. Marker's size varies with the calculated percentage reduction in PM_{10} in the absence of livestock units.

concentrations of pollutants. Our simulation showed that livestock presence is expected to cause sensitive deterioration in air quality for a sizeable share of the region's population. Hence, the study provides insights into the potential impact of changing livestock 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 practices available in the industry to prevent harmful effects on individual health and guide the evolution of the industry onto a more sustainable path.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jacopo Lunghi reports financial support was provided by Cariplo Foundation. Lara Aleluia Da Silva Reis reports financial support was provided by Cariplo Foundation. Maurizio Malpede reports financial support was provided by Cariplo Foundation.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. 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 - Swine		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	16,579	13,919	13,919	109,202	109,650	109,650	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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sensor-by-quadrant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: the table reports the estimates of βa from Eq. (1), where $\boldsymbol{\Omega}$ 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 PBLH, 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 - Swine		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	16,579	13,919	13,919	109,202	109,650	109,650	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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sensor-by-quadrant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: the table reports the estimates of β_a from Eq. (1), where $\mathbf{\Omega}$ is populated using linear weights. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average PBLH, 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 - Swine		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	16,579	13,919	13,919	109,202	109,650	13,919	3299	2790	13,919
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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sensor-by-quadrant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: the table reports the estimates of βa from Eq. (1), where $\mathbf{\Omega}$ is populated using Gaussian weights, with maximum radius 50 km. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average PBLH, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
*$p < 0.05$.
*** $p < 0.001$.
** $p < 0.01$.

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 - Swine		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	16,579	13,919	13,919	109,202	109,650	109,650	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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sensor-by-quadrant FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: the table reports the estimates of βa from Eq. (1), where $\mathbf{\Omega}$ is populated using Gaussian weights, with maximum radius 60 km. Weather controls include temperature, wind direction, wind speed, rainfall, radiance, humidity, and average PBLH, interacted with each other up to three lags. Robust standard errors are reported in parentheses.
*$p < 0.05$.
*** $p < 0.001$.
** $p < 0.01$.

Appendix B. Appendix Figures

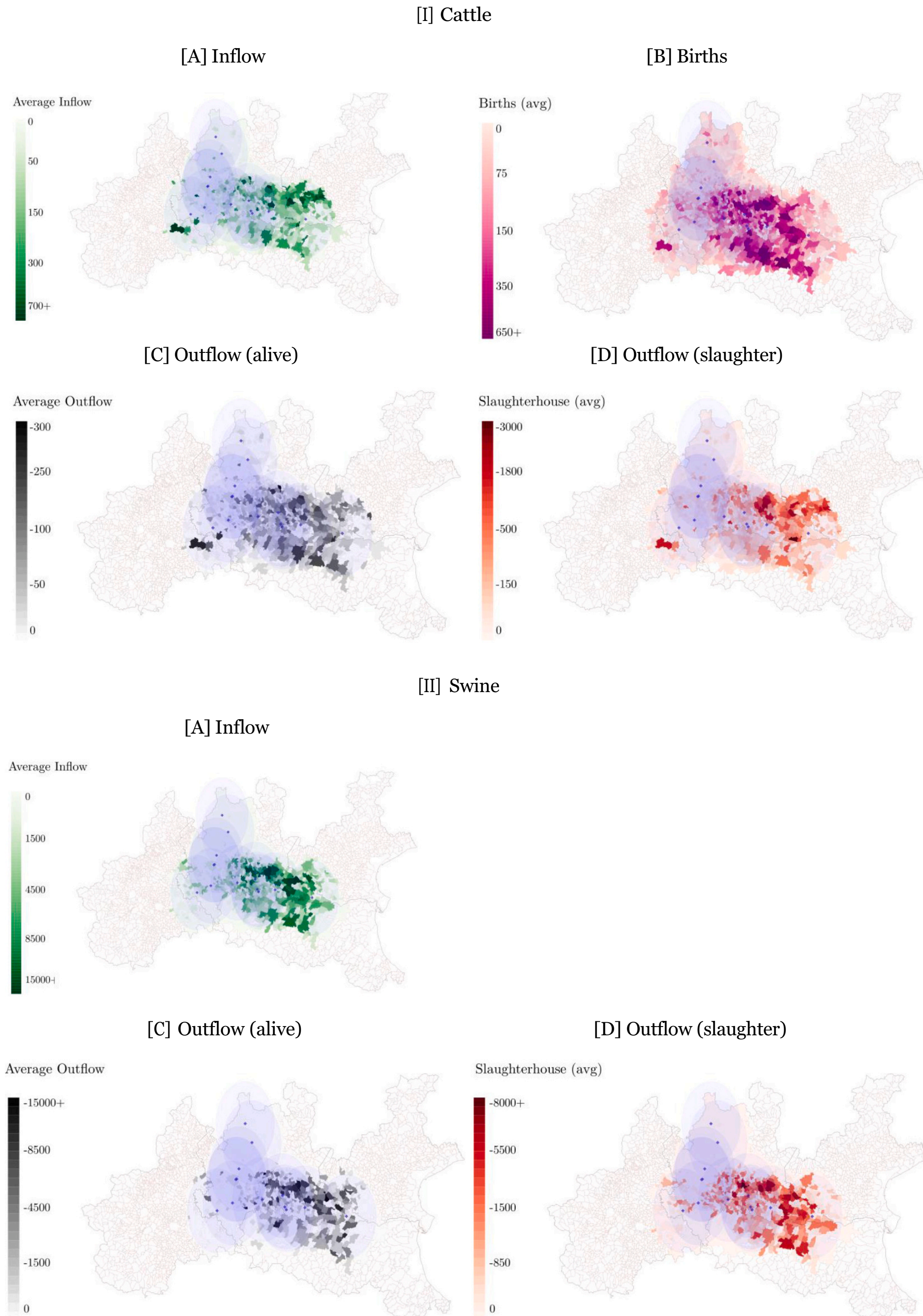

Fig. A2.1. Livestock movements around stations - Sample averages (2015–2020).
Notes: the figure plots the average monthly inflows (A), births (B), outflows (C), and slaughtered units (D) of cattle [I] and swine [II] throughout the sample period. Birth data is not separable from the overall inflow of swine. Animals displaced for slaughtering purposes are considered as an immediate depletion of the municipality's stock. Blue circles represent circular areas around sensors which includes municipalities within a 50 km radius of each station. For brevity, the figure is only plotted for NH_3 stations.

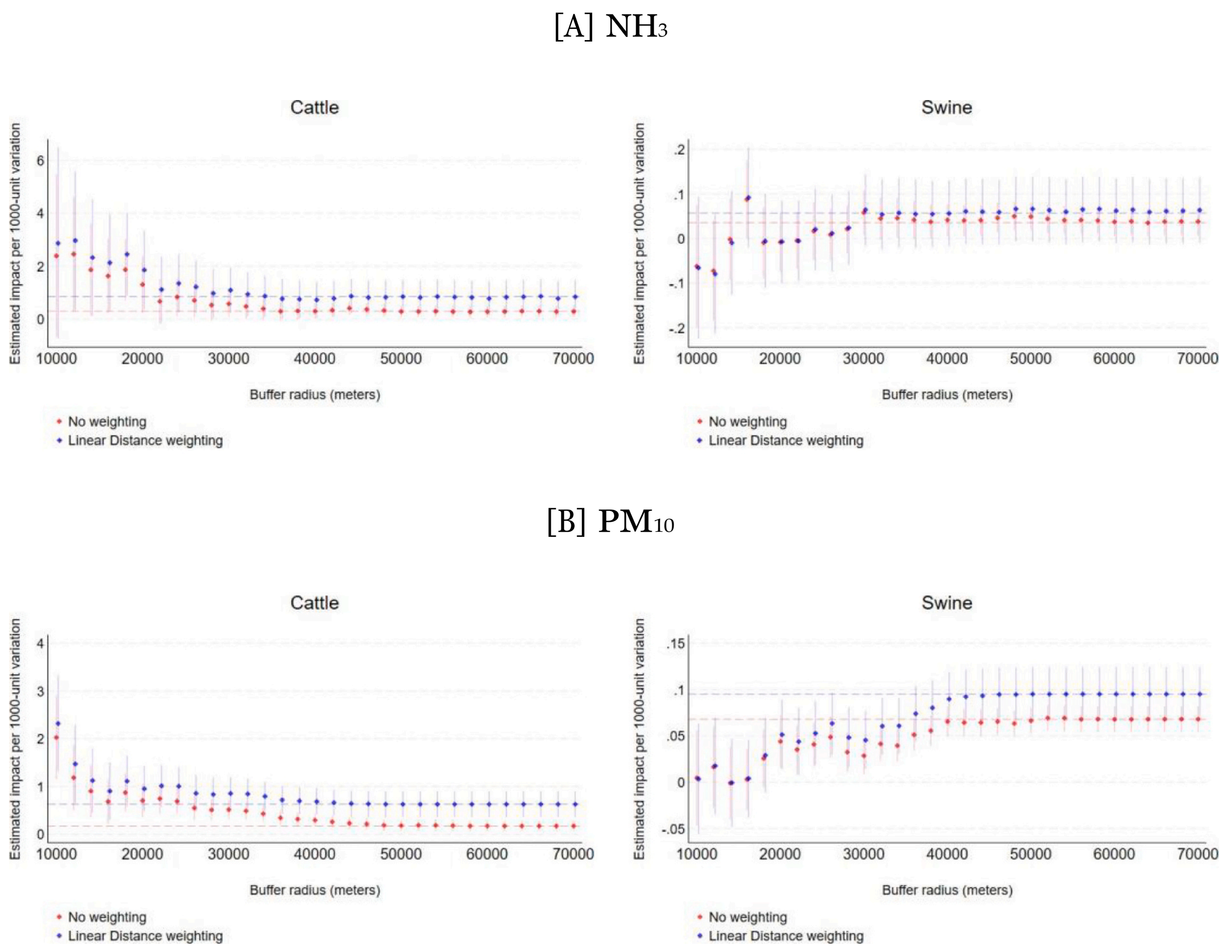

Fig. A2.2. Estimates sensitivity to expanding circular areas.
Notes: the figure shows the estimates of βa from Eq. (1), estimated using increasing values of $\bar{r}$, at 2 km increment. Hence, only the variation in livestock units within $\bar{r}$ distance from the sensor is used to explain variation in pollutant concentrations. Weather controls (temperature, wind direction, wind speed, rainfall, radiance, humidity, average PBLH, interacted with each other and up to three lags), month, year, and sensor-by-quadrant fixed effects are included. Robust standard errors are reported.

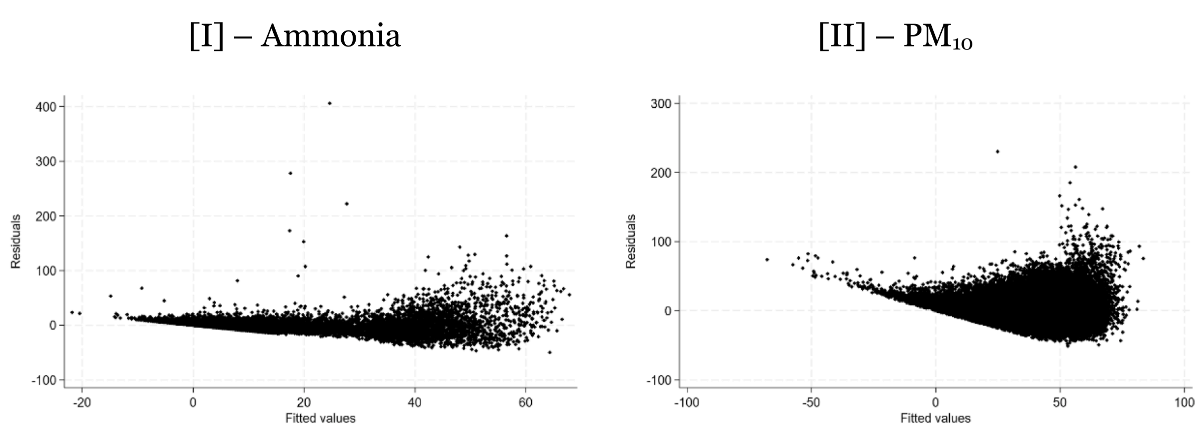

Fig. A2.3. Model residuals and fitted values.
Notes: the figure plots the residuals of our model versus fitted values. Both variation in cattle ande swine units is included in absence of weighting (corresponding to columns 3 and 6 in Table 3), and the plot is reported for ammonia (Panel I) and PM_{10} (Panel II). The plots show a rather linear trend in residuals, with increased variance toward the right end of the fitted values distribution, supporting the correction for heteroskedasticity in our standard errors.

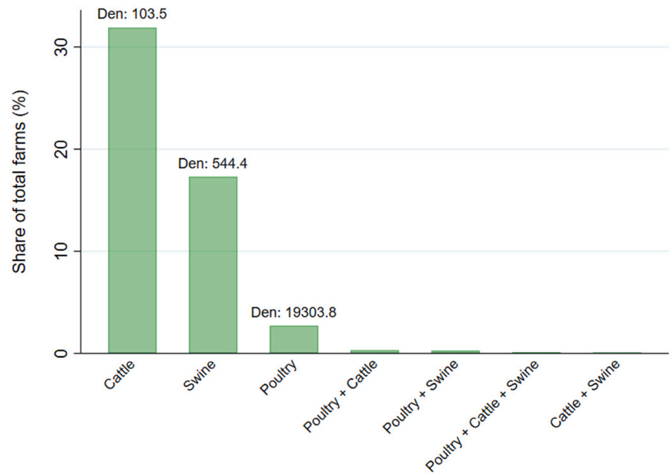

Fig. A2.4. Multi-animal farming incidence.
Notes: the figure reports the share of farms in the Lombardy region specializing in each combi- nation of the most prevalent farming animals: cattle, pigs, and chicken.

Source: ISTAT, 2010 Agricultural Census.

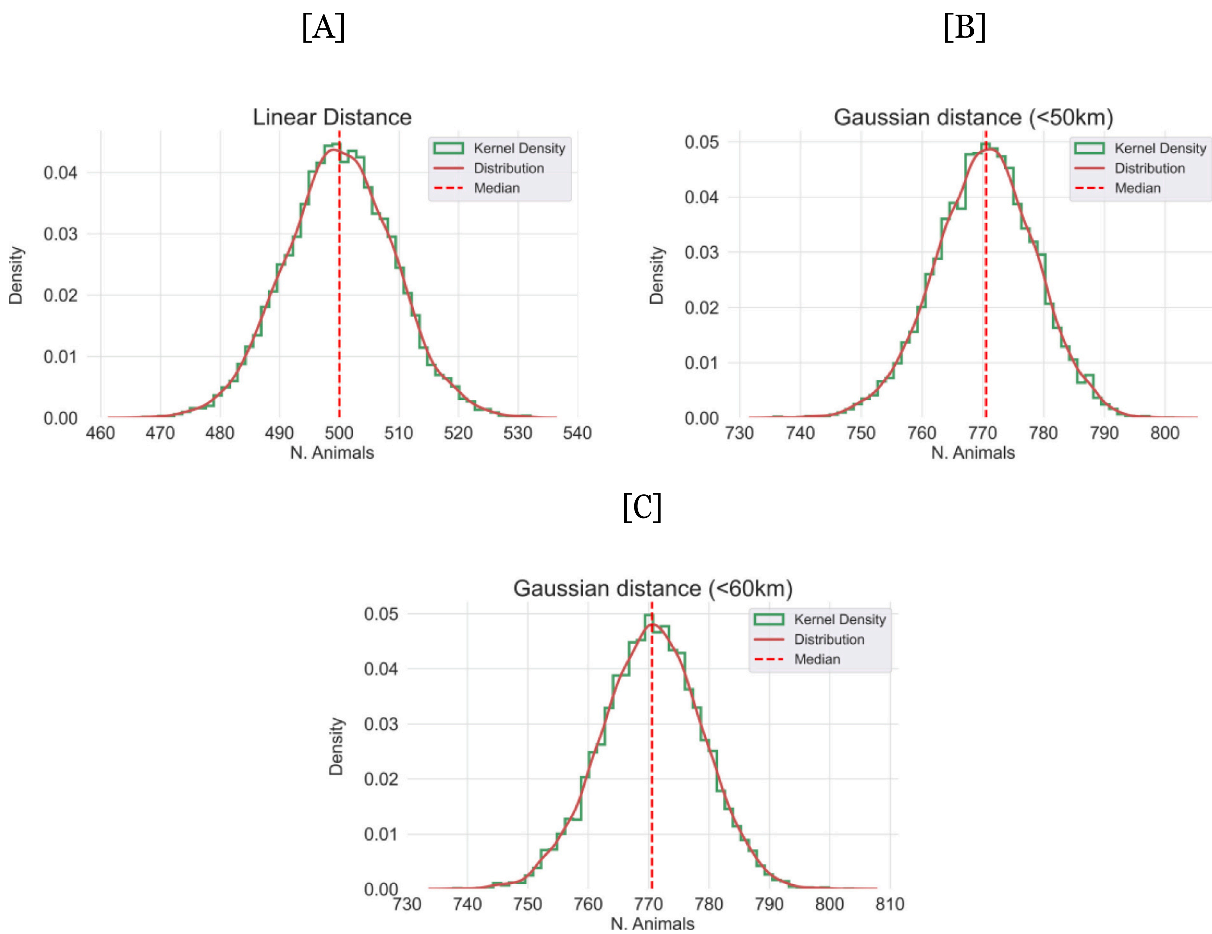

Fig. A2.5. Distributions of simulated weighted variation in livestock units (quadrant).
Notes: the figure reports the resulting distribution of a 10,000 iterations simulation of $\Delta L \times \boldsymbol{\Omega}$, where ΔL is a 1000-unit positive variation around a station. A unit is located at random distance $\widetilde{d} \sim U(0, \overline{r})$. It is then weighted through $\boldsymbol{\Omega}$ according to three different specifications: linear (A), Gaussian <50 km (B), Gaussian <60 km (C). The resulting headcount distribution, corresponding kernel density, and median outcome are plotted.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2024.107456.

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