Persistent inequalities in industrial pollution exposure across neighbourhoods in England and Wales

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Abstract:

Industrial pollution has declined in many high-income countries, yet it remains unclear whether these gains have reduced local environmental inequalities. We analyse the distribution of industrial pollution across neighbourhoods in England and Wales using facility-level data from the United Kingdom Pollutant Release and Transfer Register between 2009 and 2019. Reported emissions of regulated pollutants released to air, land, and water are combined into a common human-toxicity metric and linked to neighbourhood socioeconomic characteristics. Despite substantial national emission reductions, the spatial distribution of pollution exposure remains highly persistent: neighbourhoods that were most exposed at the start of the period remain among the most exposed a decade later. Industrial pollution shows a non-linear relationship with income, with chemical toxicity peaking in middle-income neighbourhoods and particulate matter most concentrated in lower-income areas. Higher educational attainment is consistently associated with lower levels of pollution.

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Main

Industrial pollution is not only an environmental and public health challenge but also a question of how environmental risks are distributed across communities. Many high-income countries have achieved substantial reductions in aggregate industrial emissions over recent decades. However, far less is known about whether these aggregate declines translate into spatial convergence in exposure to facility-level chemical pollution, particularly for pollutants released to land and water, or whether historical patterns of local exposure persist over time.

A growing body of evidence links industrial pollution to adverse health outcomes, including elevated risks of cancer, respiratory disease, and cardiovascular mortality in populations living near polluting facilities. Fine particulate matter alone is estimated to account for millions of premature deaths globally each year, while releases of heavy metals and organic contaminants pose long-term risks to both human and ecosystem health (McDuffie et al., 2021; Briggs, 2003). Understanding who bears these industrial pollution burdens, and how they evolve over time, is therefore central to debates on environmental justice, public health, and sustainable development.

Research on the distributional dimensions of pollution exposure is most developed in the United States, where studies consistently show that low-income and marginalised communities face higher exposure to air pollution and industrial emissions (Ard, 2015; Banzhaf, Ma & Timmins, 2019; Tessum et al., 2021; Currie, Voorheis & Walker, 2023). These patterns are commonly attributed to a combination of historical siting decisions, differences in land and housing prices that shape where firms locate and households live, unequal political influence in permitting processes, and disparities in regulatory enforcement. However, this literature has focused predominantly on ambient air pollutants and has largely characterised inequality using linear income or demographic relationships. A small number of economic studies suggest that pollution–income relationships may be non-linear, reflecting how industrial activity is distributed across space rather than declining monotonically with income. Using U.S. data, these studies show that industrial activity and toxic releases can peak in middle-income communities rather than being concentrated solely in the poorest areas (De Silva, Hubbard & Schiller, 2016; De Silva et al., 2021). Evidence on such non-linear patterns remains limited and geographically narrow, leaving open the question of whether they generalise across pollutants, time, and institutional settings.

Outside the United States, evidence on environmental justice remains more limited, particularly for industrial chemical pollution beyond air quality and for analyses that track how inequalities evolve over time. In the United Kingdom, existing studies have documented associations between ambient air pollution and neighbourhood deprivation (Mitchell & Dorling, 2003; Briggs, Abellan & Fecht, 2008; Pearce et al., 2010; Tonne et al., 2018), as well as unequal benefits from improvements in air quality (Mitchell, Notman & Mullin, 2015). Yet three important gaps remain. First, most analyses focus narrowly on particulate matter or nitrogen dioxide, overlooking the wide range of toxic substances released by industrial facilities to land and water. Second, evidence is largely cross-sectional, offering limited insight into whether environmental inequalities persist, or converge as economies restructure and regulatory frameworks evolve. Third, few studies adopt an explicitly economic perspective that allows pollution exposure to vary non-linearly across the income distribution.

This study addresses these limitations by providing a comprehensive analysis of industrial chemical pollution inequalities in England and Wales. Using facility-level data from the United Kingdom Pollutant Release and Transfer Register between 2009 and 2019, we compile emissions of 91 regulated pollutants across air, land, and water. To enable comparison across heterogeneous substances, we convert reported releases (with characterised health effects) into a common human-toxicity metric based on internationally standardised life-cycle impact assessment methods. These toxicity indicators capture potential health impacts associated with chemical releases rather than realised individual exposure, allowing consistent aggregation across pollutants and locations. We link these data to detailed socioeconomic information for more than 7,000 neighbourhoods, defined at the level of Middle Layer Super Output Areas, and examine how industrial activity and neighbourhood-level pollution exposure vary across income and education levels over time.

Our analysis advances the existing literature in three ways. First, we adopt a dynamic perspective, tracking neighbourhood-level pollution patterns over a full decade to assess the persistence of environmental inequalities in the context of declining national emissions. Second, we broaden the scope of analysis beyond ambient air pollution to consider a wide range of industrial chemical releases with characterised human-health impacts. Third, we introduce an explicitly economic framework, estimating the functional relationship between household income and local pollution exposure rather than restricting attention to comparisons between broad socioeconomic groups.

We document three central findings. First, despite substantial national reductions in industrial emissions, the spatial distribution of industrial pollution is highly persistent: neighbourhoods that were most polluted at the beginning of the period (2009) remain, on average, among the most exposed a decade later, in 2019. Second, industrial pollution exhibits a non-linear relationship with income. Rather than declining monotonically with level of income, industrial presence and chemical toxicity peak in middle-income communities, while particulate matter emissions are most concentrated in lower-income areas. Third, higher educational attainment is consistently associated with lower chemical toxicity and particulate matter across income levels.

By showing that aggregate emission reductions do not necessarily translate into spatial convergence in environmental burdens, this study highlights the importance of considering distributional outcomes alongside national pollution targets. The socioeconomic patterns observed for particulate matter and chemical toxicity further highlight that “industrial pollution” is not a single phenomenon: particulate emissions and chemical toxicity are associated with different segments of the income distribution, reflecting differences in industrial activity and regulation. These findings have implications for the design of environmental policy, suggesting that pollutant-specific and spatially targeted interventions may be necessary to address persistent inequalities in industrial pollution exposure.

Results

Industrial pollution data and reporting facility classification

We analyse how industrial pollution in England and Wales is distributed across space at the level of Middle Layer Super Output Areas (MSOAs), neighbourhood-scale geographic units defined by the UK Office for National Statistics. Our focus is on how industrial pollution patterns relate to local socioeconomic characteristics.

We draw on the UK Pollutant Release and Transfer Register (UK-PRTR), which provides nationwide, facility-level information on emissions from large industrial sources over time. Because reporting is triggered by pollutant-specific thresholds, facilities may report intermittently despite continuous operation. To distinguish long-term industrial presence from year-specific reported emissions, we classify installations as potential reporters or actual reporters, allowing us to separate the spatial footprint of industrial activity from annual variation in reported emissions. *Potential reporters* are facilities that appear at least once during the study period and are treated as present in their MSOA throughout their operational window. *Actual reporters* are facilities that report emissions in a given year, reflecting contemporaneous releases above regulatory thresholds.

Spatial persistence of industrial activity

Building on this distinction, we focus on four indicators: the number of potential reporters, the number of actual reporters, human-toxicity impacts, and PM_{10} emissions: the number of potential reporters, the number of actual reporters, human-toxicity impacts, and PM_{10} emissions. Potential reporters capture the long-term spatial footprint of industrial installations, while actual reporters reflect year-specific emissions that exceed regulatory reporting thresholds. Human-toxicity impacts and PM_{10} emissions measure realised pollution associated with this industrial activity.

Because industrial pollutants differ greatly in toxicity and physical properties, we convert emissions into a common health-impact metric using the Amalur Environmental Impact System. Emissions of 55 substances are expressed in Comparative Toxic Units for human health (CTUh), which quantify the potential health burden associated with chemical releases. Facility-level toxicity impacts are aggregated to the MSOA level (see Methods).

As an additional indicator, we analyse emissions of particulate matter smaller than 10 microns (PM_{10}), a major air-quality pollutant with well-established links to respiratory and cardiovascular disease. To reflect atmospheric dispersion, MSOA-level PM_{10} measures incorporate distance-weighted contributions from neighbouring areas (Methods).

Across the study period, industrial presence is highly persistent in space. MSOAs without potential reporting facilities in 2009 had an 80% probability of remaining industrially inactive in 2019, while MSOAs hosting industrial installations typically contained between one (10th percentile) and four (90th percentile) facilities throughout the decade (Supplementary Fig. S.1). This stability indicates that the spatial footprint of industrial activity is largely fixed over the study period, allowing subsequent analyses to distinguish persistent location patterns from year-to-year variation in reported emissions.

Trends and spatial concentration of industrial pollution

Despite substantial national declines in industrial pollution, pollution levels remain highly uneven across local areas. We observe that human toxicity impacts and PM_{10} emissions reached a peak in 2013 and 2012, respectively. Since then, both measures have fallen substantially over time. Between 2009 and 2019, average human toxicity impacts fell by approximately 43.6% while PM_{10} emissions fell 66%. However, this aggregate decline masks substantial and persistent heterogeneity, as we will illustrate in Figures 1 and 2.

In 2019, 6,571 out of 7,201 MSOAs exhibit zero reported human toxicity, reflecting the absence of reporting industrial emissions above PRTR thresholds in those areas. Among MSOAs with strictly positive human toxicity, impacts are highly concentrated: the mean is 1.38 CTUh, with a 10th percentile of 0.00016 CTUh and a 90th percentile of 1.43 CTUh. This spatial disparity is also illustrated by the persistent clustering of PM_{10} emissions across MSOAs in 2009 and 2019 (Supplementary Fig. S.2).

Although neither CTUh nor MSOA-level PM_{10} emissions correspond directly to regulatory thresholds, their magnitudes provide insight into the potential severity of remaining pollution in 2019. Human toxicity values exceeding 1 CTUh correspond to an expected increase of more than one statistical disease case in the exposed population, suggesting that impacts in affected MSOAs are unlikely to be negligible (Rosenbaum et al., 2008; Jolliet & Fantke, 2015). Similarly, although PM_{10} emissions expressed in tonnes appear numerically small, epidemiological evidence indicates adverse health effects even at low ambient concentrations, with no established safe exposure threshold (WHO, 2021). Together, these magnitudes indicate that, despite substantial national declines, residual industrial pollution in a subset of MSOAs remains of potential public health relevance.

Persistence and evolution of pollution ranks across neighbourhoods

Despite substantial declines in national pollution levels, the relative ordering of neighbourhoods by industrial pollution exposure remains remarkably stable over time (Fig. 1). MSOAs with the highest human-toxicity impacts or PM_{10} emissions in 2009 remain, on average, among the most exposed in 2019, indicating strong rank persistence for both pollutants.

However, PM_{10} exhibits partial convergence toward the median: neighbourhoods that were highly polluted in 2009 tend to move (slightly) down the ranking by 2019, while those with initially low PM_{10} emissions tend to move (slightly) up. In contrast, human-toxicity impacts display larger shifts in both directions across the distribution, consistent with greater dispersion over time.

Distributional dynamics also differ across pollutants (Fig. 2). For PM_{10}, spatial inequality, as measured by the gap between the 90th and 10th percentiles, declines over the study period, consistent with a broad-based reduction in exposure disparities. In contrast, inequality in human-toxicity impacts decreases only temporarily and begins to widen again after 2017, suggesting that gains in reducing chemical pollution burdens are uneven and may be reversing in the most affected areas, even as aggregate emissions continue to fall.

The strong persistence and new divergence in pollution exposure raise the question of whether these spatial patterns systematically align with differences in local socioeconomic conditions, a central concern in debates on environmental inequality.

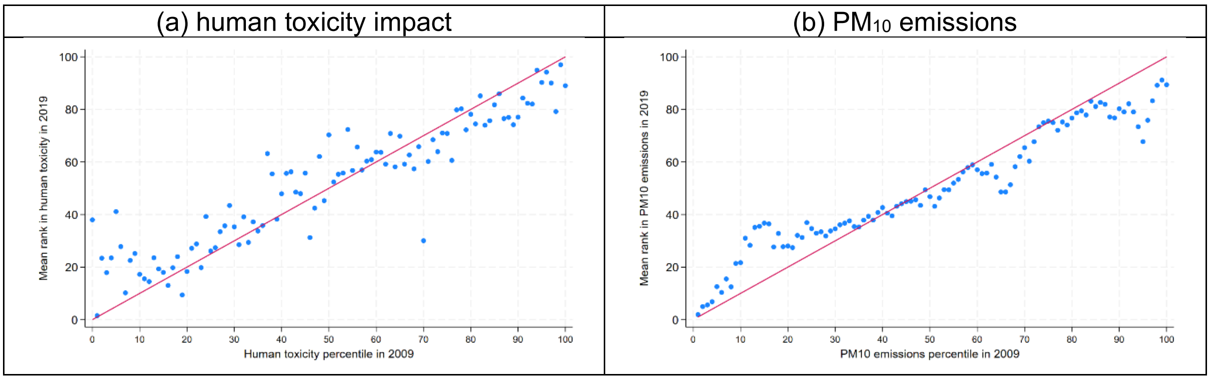

Figure 1: Persistence of neighbourhood pollution rankings over time. The figure plots the percentile rank of MSOAs based on human-toxicity impacts (a) and PM_{10} emissions (b) in 2009 (horizontal axis) against their mean percentile rank in 2019 (vertical axis). The red 45-degree line indicates no change in relative rank over time. Points above (below) the line indicate an increase (decrease) in relative pollution exposure. For both pollutants, MSOAs that were among the most polluted in 2009 remain, on average, among the most polluted a decade later, indicating strong persistence in the spatial distribution of industrial pollution.

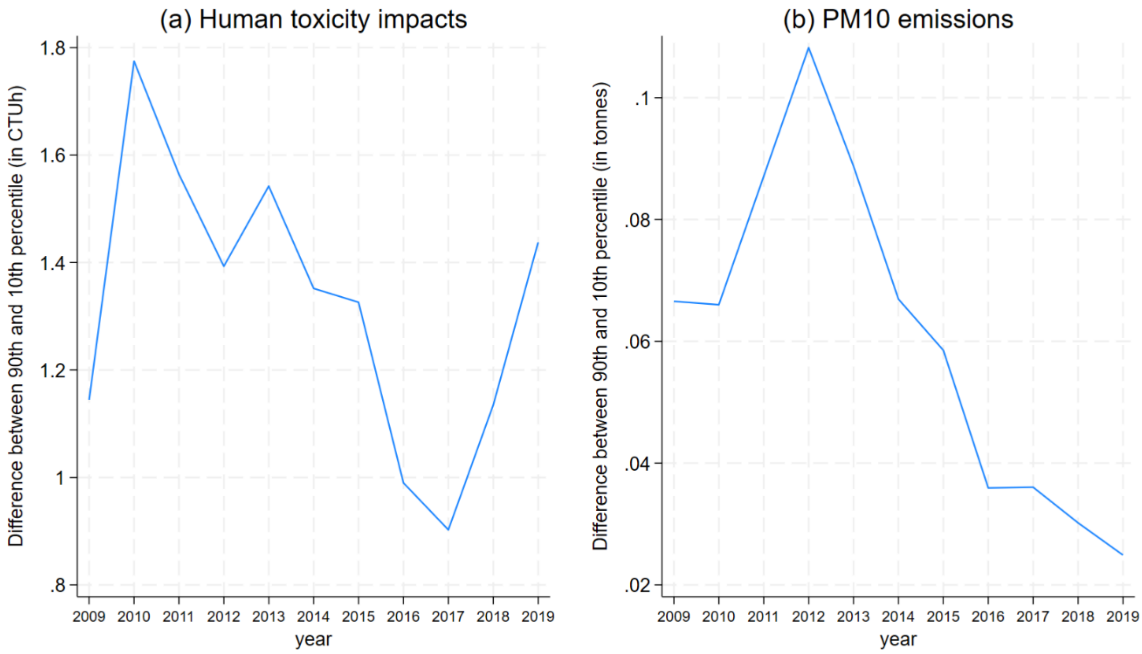

Figure 2: Evolution of spatial inequality in industrial pollution exposure. The figure shows the difference between the 90th and 10th percentiles of MSOA-level human-toxicity impacts (a) and PM_{10} emissions (b) between 2009 and 2019. For PM_{10}, the gap narrows steadily over time, indicating a reduction in spatial inequality. In contrast, inequality in human-toxicity impacts declines initially but begins to increase again after 2017.

Adding socioeconomic patterns

To address this question, we examine how industrial activity and pollution exposure are distributed across neighbourhoods with different socioeconomic profiles, focusing primarily on median household income at the MSOA level.

Before turning to the regression analysis, Figure 3 groups MSOAs into household-income bands for 2009 and 2019 and reports the distribution of industrial activity and toxic releases across the income spectrum.

Two clear patterns emerge. First, industrial installations are distributed across nearly the entire income distribution in both years, rather than being concentrated solely in the lowest-income neighbourhoods. Second, MSOAs experiencing positive human-toxicity impacts exhibit a similarly broad income profile. Together, these descriptive patterns indicate that persistent industrial pollution exposure is not exclusively a feature of the poorest communities.

However, these patterns are purely descriptive and do not establish whether pollution exposure varies systematically with income once other neighbourhood characteristics are taken into account. We therefore turn to a regression analysis to isolate the relationship between local socioeconomic conditions and industrial activity and emissions, conditional on observable area-level controls.

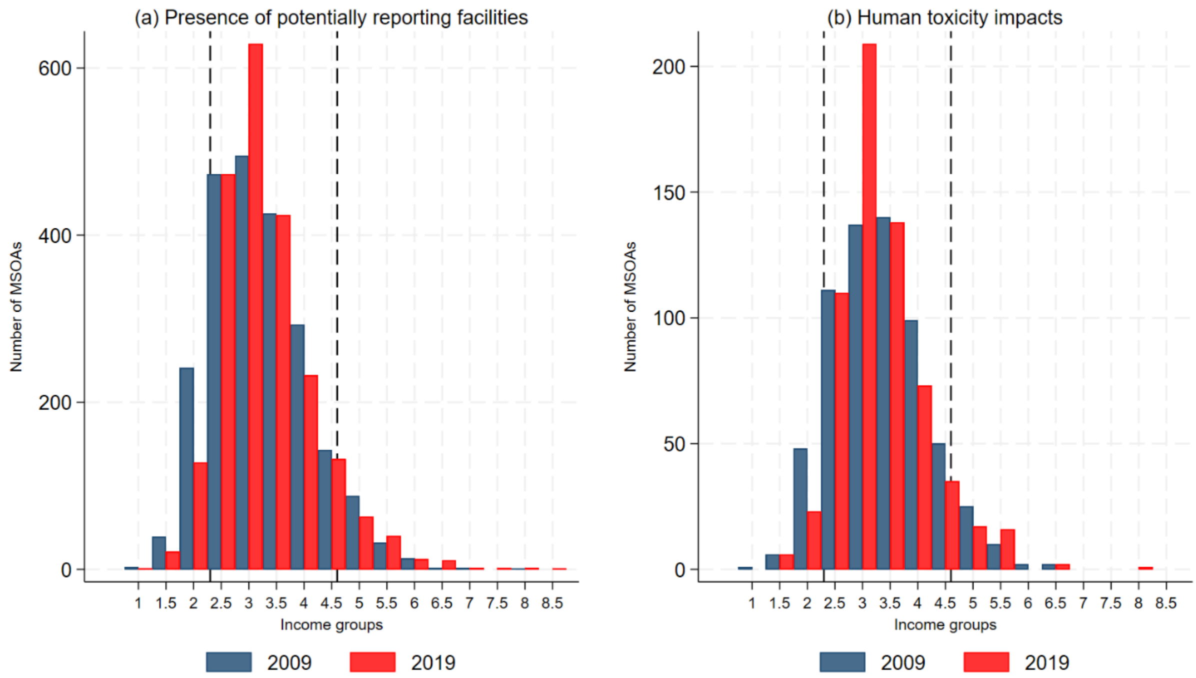

Figure 3: Distribution of industrial activity and toxic releases across neighbourhood income groups. MSOAs are grouped into £5,000 household-income bands in 2009 and 2019, ranging from £10,000–£15,000 (group 1) to above £85,000 (group 8.5). Vertical dashed lines indicate the 10th and 90th percentiles of the MSOA income distribution.
a, Number of MSOAs in each income group containing at least one potentially reporting industrial facility. **b**, Number of MSOAs in each income group with strictly positive human-toxicity impacts (CTUh > 0). Blue bars correspond to 2009 and red bars to 2019.
Industrial facilities and associated toxic releases are observed across nearly the entire income distribution in both years, indicating that exposure is not confined to the lowest-income neighbourhoods.

Income and industrial facility location

We first assess whether the descriptive income patterns in industrial activity persist once other neighbourhood characteristics are taken into account. To do so, we estimate regression models that relate neighbourhood income to the presence of industrial facilities, while controlling for population size, land area, educational attainment, local amenities, and year effects (see Methods).

Because the outcomes are non-negative and highly skewed, we use regression models appropriate for count data. To allow for non-linear relationships, income enters flexibly through linear, quadratic, and cubic terms. Table 1 summarises the results for both potential reporting facilities, which capture long-term industrial presence, and facilities reporting emissions in a given year.

Across specifications, the income terms are jointly significant (p-value < 0.001), and their signs imply an inverted U-shaped relationship between income and industrial facility counts. Industrial presence rises with neighbourhood income up to a turning point at approximately £35,000, close to the median of the MSOA income distribution, before declining in higher-income areas. As a result, middle-income neighbourhoods host the highest concentration of industrial installations, whereas both lower- and higher-income areas tend to contain fewer facilities. This pattern indicates that industrial activity is not disproportionately concentrated in the poorest neighbourhoods, but instead peaks in the middle of the income distribution.

Income and pollution intensity

We next examine whether the inverted U-shaped pattern observed for facility counts extends to realised pollution. Table 2 reports results for human-toxicity impacts and PM_{10} emissions. For chemical pollution, we distinguish between total human-toxicity impacts and impacts associated with substances classified as cancer-causing or non-cancer-causing under the Amalur Environmental Impact System (see Methods).

Human-toxicity measures contain a large number of zero observations, reflecting the absence of reported emissions above regulatory thresholds in many neighbourhoods. We therefore use regression models designed to account for censoring, while PM_{10} emissions are analysed in logarithmic form using linear regression (see Methods). Income is again modelled flexibly to capture potential non-linearities.

Across all pollution measures, the income terms are jointly significant, and the estimated coefficients imply inverted U-shaped relationships between income and pollution exposure. However, the location of the peak differs markedly across pollutants. PM_{10} emissions peak at relatively low-income levels (around £25,500, corresponding to roughly the 10th percentile of the MSOA income distribution in 2019) after which emissions decline steadily across most of the income range. In contrast, human-toxicity impacts peak at substantially higher income levels, around £43,500, above the 75th percentile of the income distribution.

These differences indicate that particulate matter and chemical toxicity respond differently to local socioeconomic conditions. While the poorest neighbourhoods experience the highest PM_{10} emissions, human-toxicity impacts rise through low- and middle-income communities and are most concentrated in middle-income areas before declining in the highest-income neighbourhoods.

Educational attainment and pollution exposure

Although income is the primary focus of the analysis, the regression framework also allows us to examine other socioeconomic characteristics associated with pollution exposure. One such factor is educational attainment, measured as the share of adults with higher-education qualifications in each neighbourhood.

Controlling for income and the full set of neighbourhood characteristics, higher educational attainment is consistently associated with lower industrial pollution across all outcome measures (Tables 1 and 2). For example, a 5-percentage-point increase in the share of adults with higher education is associated with approximately 6% lower PM_{10} emissions.

Variables	Number of potential polluters		Number of polluters	
	(1)	(2)	(3)	(4)
Income (β_1)	0.702***	1.426***	2.811***	3.660***
	(0.209)	(0.215)	(0.268)	(0.404)
$Income^2$ (β_2)	-0.127**	-0.261***	-0.501***	-0.659***
	(0.050)	(0.042)	(0.057)	(0.075)
$Income^3$ (β_3)	0.005	0.014***	0.025***	0.034***
	(0.004)	(0.003)	(0.004)	(0.004)
Population	0.112***	0.112***	0.080***	0.077***
	(0.005)	(0.007)	(0.007)	(0.011)
Higher education ratio	-3.891***	-4.379***	-4.973***	-4.191***
	(0.259)	(0.349)	(0.429)	(0.599)
Number of amenity establishments		0.001***		0.000
		(0.000)		(0.000)
MSOA area	0.003***	0.003***	0.004***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Year effects	Yes	Yes	Yes	Yes
Observations	79,211	28,804	79,211	28,804
Wald χ^2	2,470.20	916.06	1,332.02	462.17
H_0: $\beta_1 + \beta_2 + \beta_3 = 0$ (χ^2 probability)	0.000	0.000	0.000	0.000

Table 1: Income and the spatial distribution of industrial facilities. Poisson pseudo-maximum likelihood estimates relating neighbourhood household income to the number of industrial installations at the MSOA level. Columns (1)–(2) report results for the number of potential reporting facilities, capturing long-term industrial presence, while columns (3)–(4) report results for the number of facilities reporting emissions in a given year. Income enters flexibly through linear, quadratic, and cubic terms, allowing for non-linear relationships. All specifications include year fixed effects and neighbourhood-level controls. Robust standard errors are shown in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Income is in £10,000s, population is in 1,000s, and MSOA area is in millions of hectares.

Variables	Human toxicity	Non-Cancer	Cancer	Log(PM_{25})	Human toxicity	Non-Cancer	Cancer	Log(PM_{25})
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income (in 10,000)	17.233***	17.612***	0.084**	0.400***	20.075***	20.254***	0.103***	0.875***
	(1.933)	(1.938)	(0.042)	(0.090)	(2.139)	(2.145)	(0.037)	(0.148)
Income^2 (in 10,000)	-3.039***	-3.098***	-0.023**	-0.109***	-3.486***	-3.514***	-0.021***	-0.192***
	(0.428)	(0.428)	(0.009)	(0.021)	(0.426)	(0.426)	(0.008)	(0.032)
Income^3 (in 10,000)	0.162***	0.165***	0.002***	0.008***	0.182***	0.184***	0.001**	0.012***
	(0.031)	(0.031)	(0.001)	(0.001)	(0.027)	(0.027)	(0.000)	(0.002)
Population (in 1,000)	0.527***	0.516***	0.015***	0.013***	0.393***	0.386***	0.008***	0.019***
	(0.058)	(0.058)	(0.001)	(0.003)	(0.069)	(0.070)	(0.001)	(0.005)
Higher education ratio	-37.718***	-37.526***	-0.510***	-1.285***	-28.750***	-28.429***	-0.304***	-1.383***
	(3.942)	(3.948)	(0.103)	(0.119)	(4.108)	(4.109)	(0.077)	(0.193)
Number of amenity establishments					0.001	0.001	0.000**	-0.000**
					(0.003)	(0.003)	(0.000)	(0.000)
MSOA area (in millions of hectares)	0.060***	0.061***	0.000***	0.006***	0.048***	0.048***	0.000***	0.007***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)
Year effects	Yes	Yes	Yes	0.400***	Yes	Yes	Yes	Yes
Observations	79,211	79,211	79,211	79,211	28,804	28,804	28,804	28,804
LR χ^2	2,389.12	2,399.98	396.24	-137,749	979.31	983.57	149.32	-51,534
Left-censored observations	72,143	72,200	76,834		26,230	26,246	27,974	
H_0: $\beta_1 + \beta_2 + \beta_3 = 0$ (χ^2 probability)	0.000	0.000	0.020	0.000	0.000	0.000	0.028	0.000

Table 2: Income and industrial pollution exposure. Regression estimates relating neighbourhood household income to industrial pollution intensity at the MSOA level. Columns (1)–(3) report Tobit estimates for total human-toxicity impacts and their non-cancer and cancer components, reflecting the large share of zero observations. Columns (4) and (8) report ordinary least squares estimates for log PM_{10} emissions. Income is modelled flexibly using linear, quadratic, and cubic terms. All models include year fixed effects and neighbourhood-level controls. Columns (5)-(8) are estimated on a restricted sample covering 2016–2019, reflecting data availability for neighbourhood amenity establishments. Robust standard errors are shown in parentheses. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1. Income is in £10,000s, population is in 1,000s, and MSOA area is in millions of hectares.

Discussion

Despite substantial national reductions in PM_{10} emissions and human-toxicity impacts over the past decade, our results show that the relative spatial distribution of industrial pollution has remained stable. Communities that were most polluted in 2009 remain, on average, among the most exposed in 2019. This persistence in relative rankings indicates that aggregate emission declines have not translated into spatial convergence in environmental burdens. Instead, pollution exposure appears to be shaped by long-term local factors, such as industrial legacies, land-use patterns, and regulatory thresholds, that continue to influence where polluting activities are located.

By linking facility-level emissions to local socioeconomic data, our analysis reveals a robust inverted U-shaped relationship between income and multiple dimensions of industrial activity, including the presence of polluting facilities, PM_{10} emissions, and human-toxicity impacts. This pattern challenges the common assumption that pollution burdens decline monotonically with income, showing instead that industrial pollution is highest in middle-income areas, while both very low- and very high-income communities tend to host fewer polluting facilities. Taken together, these results indicate that environmental exposure is shaped not only by socioeconomic disadvantage, but also by the spatial organisation of industrial activity and production, which distributes pollution across the income spectrum.

Beyond this general income pattern, our results show that “industrial pollution” is not a single, uniform phenomenon: PM_{10} emissions and chemical-toxicity impacts peak in different parts of the income distribution and reflect differences in industrial activity and regulation. PM_{10} burdens are disproportionately concentrated in lower-income communities, consistent with well-documented environmental-justice patterns in air pollution exposure. In contrast, human-toxicity impacts are highest in middle-income areas. These divergent patterns likely arise because facilities responsible for fine-particulate emissions are not necessarily those generating chemical releases with high toxicity equivalents.

Beyond income, educational attainment emerges as an additional socioeconomic correlate of lower pollution exposure, even after accounting for income differences. While our analysis does not identify causal mechanisms, this association is consistent with the idea that community characteristics related to information access, political engagement, or local regulatory capacity may influence environmental outcomes. Differences in educational attainment may shape communities’ capacity to engage in planning processes, respond to permit applications, or exert pressure on local authorities and firms, pointing to channels that warrant further investigation.

Taken together, these findings have important implications for environmental justice and regulatory design. The persistence of spatial disparities despite large aggregate emission reductions suggests that policies focused solely on national or sectoral emission targets may leave underlying inequalities largely unchanged. Moreover, the fact that PM_{10} and human-toxicity impacts peak at different income levels indicates that no single socioeconomic group bears all forms of industrial pollution: low-income communities face disproportionate exposure to particulate emissions, while middle-income communities bear the highest chemical-toxicity burdens. This differentiation implies that pollutant-specific and sector-specific interventions may be more effective than uniform regulatory approaches in addressing environmental inequalities.

The stability of pollution patterns over time further points to structural features of industrial siting, production processes, and reporting frameworks that may limit the responsiveness of local environmental outcomes to aggregate regulatory change, suggesting that addressing persistent disparities will require policies that explicitly consider the spatial distribution of emissions.

Future research could examine the causal pathways linking socioeconomic characteristics and pollution exposure, assess the role of community engagement and institutional capacity in shaping industrial activity, and explore whether similar patterns arise in other national pollutant-release registries. More broadly, our results demonstrate the value of integrating detailed emissions data with granular socioeconomic information to understand not only how environmental burdens decline, but also how their distribution across communities evolves.

Methods

Geographic framework

Our unit of analysis is the Middle Layer Super Output Area (MSOA) in England and Wales. MSOAs are designed to maintain stable geographic boundaries over time. They have a minimum of 5,000 residents (2,000 households) and a maximum of 15,000 residents (6,000 households).

We use MSOA boundaries as defined by the 2011 census. In 2011, there were a total of 7,201 Middle Layer Super Output Areas (MSOA) in England and Wales. In our dataset, MSOAs have an average population of approximately 7,200. The median area of an MSOA is 3.2 km², while the mean is 21 km², the latter reflecting large rural MSOAs.

Pollution data

Because our analysis requires consistent coverage across pollutants, industrial sectors, and time, we use data from the UK Pollutant Release and Transfer Register (UK-PRTR) for the period 2009–2019. The UK-PRTR provides facility-level information on emissions from large industrial sources and requires installations to report on-site releases that exceed pollutant-specific thresholds for 91 regulated substances.

The UK-PRTR is part of an internationally harmonised reporting framework established under the UNECE Protocol on Pollutant Release and Transfer Registers. Reporting rules and pollutant definitions remained stable over the study period. Facilities are required to belong to one of 65 Annex I activities and to employ at least 10 full-time equivalent staff. Reporting is triggered only when emissions exceed pollutant-specific thresholds, which are designed to limit reporting burdens for small emitters while ensuring coverage of major pollution sources.

Because reporting is threshold-based, installations may appear intermittently in the data even if operations continue. To distinguish long-term industrial presence from year-specific reported emissions, we classify facilities into two categories. *Potential reporters* are installations that appear at least once in the UK-PRTR during 2009–2019 and are treated as present in the corresponding MSOA for all years between their first and last report. *Actual reporters* are installations that report emissions in a given year, reflecting contemporaneous releases above regulatory thresholds.

In the UK-PRTR, each facility reports at most one annual emission value per pollutant when releases exceed reporting thresholds. For a given facility and year, reported emissions therefore consist of a single quantity per pollutant. We aggregate these reported quantities across pollutants and release media using the Amalur Environmental Impact System (EIS) to construct a facility–year measure of industrial pollution.

The Amalur EIS converts raw emission quantities into environmental impact scores using internationally standardised life-cycle impact assessment methods. We focus on the human-toxicity impact category, which covers 55 pollutants with characterised health effects released to air, water, or land. For each pollutant, emissions in kilograms are multiplied by a pollutant-specific characterisation factor expressed in Comparative Toxic Units for human health (CTUh/kg). CTUh values quantify the potential increase in disease cases associated with chemical releases and allow consistent aggregation across heterogeneous substances. Facility-level human-toxicity impacts are computed by summing toxicity-equivalent emissions across all reported pollutants and release media.

Because the UK-PRTR only records emissions that exceed reporting thresholds, the absence of reported emissions for a facility in a given year does not necessarily imply zero releases. It may instead reflect emissions below reporting thresholds or other administrative factors. As no independent source of continuous facility-level emissions exists, our analysis relies exclusively on reported emissions and does not attempt to impute unreported values. Missing facility–year emissions are therefore treated as unobserved or below-threshold. As a result, estimated pollution levels should be interpreted as lower bounds on total releases, and year-to-year changes may partly reflect movements relative to reporting thresholds rather than changes in true underlying emissions.

Facility locations are provided in the UK-PRTR via postcodes, which we link to Middle Layer Super Output Areas (MSOAs). Each facility is uniquely geocoded and counted once per MSOA-year. Facilities with missing postcodes are excluded. For each MSOA and year, we compute the number of potential reporters, the number of actual reporters, total reported PM_{10} emissions, and aggregate human-toxicity impacts based on reported emissions.

To account for atmospheric transport of particulate matter, we adjust MSOA-level PM_{10} emissions to incorporate a distance-weighted average of emissions originating in neighbouring MSOAs. Adjusted PM_{10} exposure is defined as the sum of local reported emissions and an inverse-distance-weighted average (sum) of emissions from all other MSOAs, based on Euclidean distances between MSOA geometric centroids. We impose no maximum distance cutoff, and weights are normalised to sum to one.

Socioeconomic data

Annual median household income at the MSOA level is obtained from the UK Office for National Statistics (ONS). Income includes gross earnings and cash benefits and is expressed in real terms using 2009 as the base year. In our sample, average household income in 2019 is approximately £36,350. Educational attainment is measured as the share of adults aged 16 and over with higher-education qualifications (Level 4 or above), using data from the Annual Population Survey.

Additional neighbourhood-level controls include total MSOA population, obtained from the ONS, and MSOA land area (in km^2), obtained from the Open Geography Portal. In alternative specifications, we also control for local amenities, defined as the number of establishments in Arts, Entertainment, Recreation and Other Services, and in Accommodation and Food Services, based on the ONS Inter-Departmental Business Register. Amenity data are available for the period 2016–2019.

Persistence of disparities

To assess the persistence of spatial disparities in pollution exposure, we ranked MSOAs separately in 2009 and 2019 based on their human-toxicity impacts and PM_{10} emissions. MSOAs were assigned percentile ranks within each year, and for each percentile group in 2009 we computed the mean percentile rank in 2019. Figure 1 plots the average 2019 rank against the corresponding 2009 percentile, with a 45° reference line indicating perfect persistence. Deviations from the line reflect changes in relative exposure over time.

For analyses involving human-toxicity impacts (Figure 1a and the 90th–10th percentile gap in Figure 2), we restrict the sample to MSOAs with strictly positive reported toxicity in at least one of the two years. This restriction avoids distortions in rank ordering and inequality measures arising from the large mass of zero observations driven by threshold-based reporting.

Income–pollution relationships (Figure 3)

To describe how industrial activity and toxicity exposures are distributed across the income spectrum, we grouped MSOAs into £5,000 income bands using median household income. Income groups begin at £10,000–£15,000 and extend in £5,000 increments (e.g., £15,000–£20,000; £20,000–£25,000), with the same grouping applied in 2009 and 2019. Income bands are defined using contemporaneous income distributions within each year.

For each income group, we counted (i) the number of MSOAs containing at least one potentially reporting facility and (ii) the number of MSOAs with strictly positive human-toxicity impacts. These counts form the bars shown in Figure 3, separately for 2009 (blue) and 2019 (red). The vertical dashed lines indicate the 10th and 90th percentiles of the MSOA income distribution in our sample.

Regression specifications

Our regression analysis is conducted on a balanced panel of 7,201 MSOAs observed annually from 2009 to 2019.

We estimate the relationship between neighbourhood income and industrial activity or pollution exposure using three complementary models, depending on the nature of the outcome variable. In all specifications, income enters flexibly through linear, quadratic, and cubic terms to allow for non-linear relationships, and all models include year fixed effects and MSOA-clustered standard errors.

All regressions control for MSOA population, land area, educational attainment, and, where available, local amenities. Income is expressed in real terms (2009 base year). We do not include MSOA fixed effects, as our objective is to characterise cross-sectional associations between income and pollution exposure rather than within-area changes over time.

For counts of industrial facilities, we use Poisson pseudo–maximum likelihood (PPML) estimation, which is appropriate for non-negative, skewed count data and is robust to heteroskedasticity. We estimate separate models for the number of potential reporting facilities and the number of facilities reporting emissions in a given year.

The conditional mean of the outcome is specified as an exponential function of income, neighbourhood controls, and year effects:

$$\mathbb{E}[Y_{it} \mid Income_{it}, \boldsymbol{X}_{it}] = \exp(\alpha + \beta_1 \text{Income}_{it} + \beta_2 \text{Income}_{it}^2 + \beta_3 \text{Income}_{it}^3 + \boldsymbol{\gamma} \boldsymbol{X}_{it} + \tau_t),$$

Where Y_{it} denote the number of facilities (potential or actual reporters) in MSOA i at time t, $\boldsymbol{X}_{it}$ denote the set of explanatory variables, and τ_t are year dummies.

For actual pollution measures (human-toxicity impacts and PM_{10} emissions), we estimate the following linear model:

$$Y_{it} = \alpha + \beta_1 \text{Income}_{it} + \beta_2 \text{Income}_{it}^2 + \beta_3 \text{Income}_{it}^3 + \boldsymbol{\gamma} \boldsymbol{X}_{it} + \tau_t + \varepsilon_{it}$$

Where Y_{it} denote either human-toxicity impacts or PM_{10} emissions (in log). ε_{it} represents the error term.

Human-toxicity impacts exhibit a large mass of zero observations because emissions are only reported when releases exceed regulatory thresholds. As a result, observed toxicity measures are left-censored at zero. To account for this censoring, we estimate Tobit models, which allow neighbourhoods to differ both in their underlying pollution intensity and in whether reported emissions exceed reporting thresholds, without requiring assumptions about the magnitude of unreported emissions.

For PM_{10} emissions, distance-weighted adjustments ensure strictly positive values for all MSOAs. We therefore estimate log-linear ordinary least squares models for PM_{10} emissions.

Supplementary figures

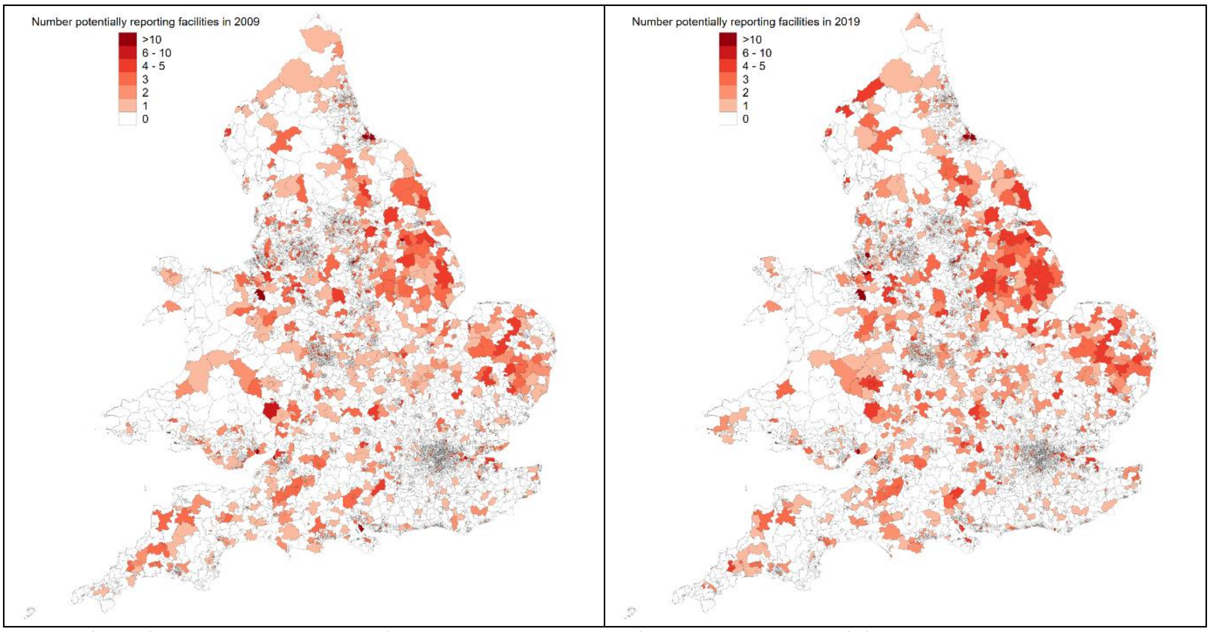

Figure S.1: Spatial distribution of potentially reporting facilities across MSOAs in England and Wales. Number of potentially reporting facilities per MSOA in 2009 (left) and 2019 (right). MSOA boundaries are shown. MSOAs without any reporting facilities are shown in white (4,951 in 2009 and 5,029 in 2019). Darker shades of red indicate a higher number of facilities. A total of 4,642 facilities are observed in 2009 and 4,647 in 2019.

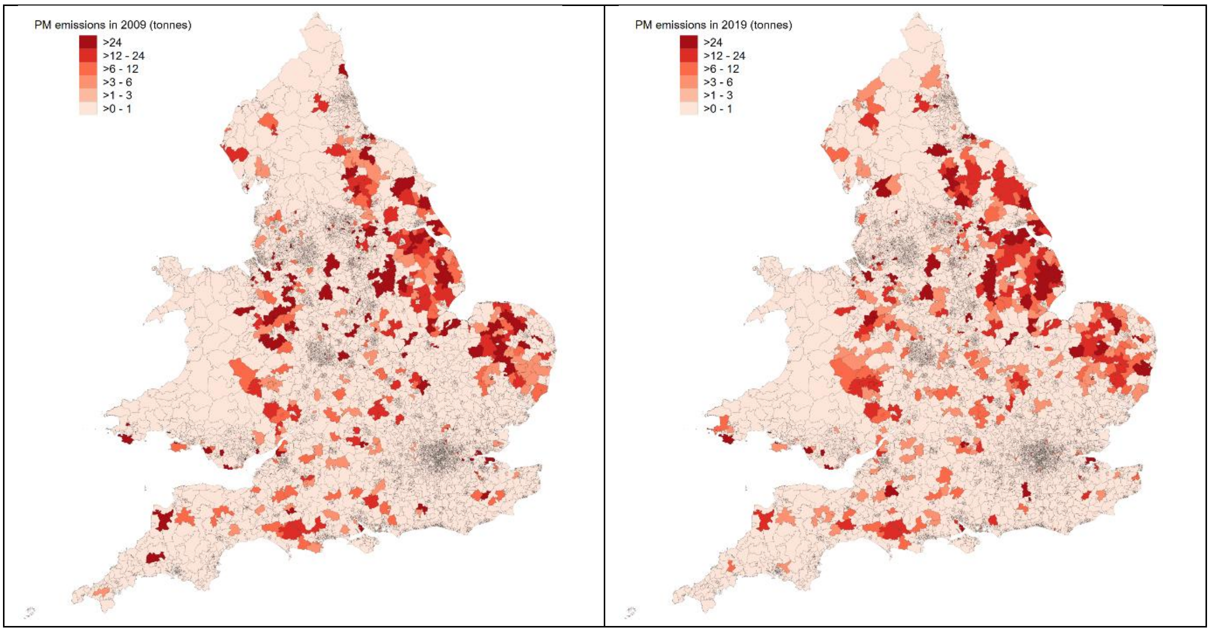

***Figure S.2: Spatial distribution of PM_{10} emissions across MSOAs in England and Wales*.** PM_{10} emissions (in tonnes) aggregated at the MSOA level for 2009 (left) and 2019 (right). Darker shades of red indicate higher levels of emissions. MSOA boundaries are shown. Emissions reflect distance-weighted contributions from facilities located within and in neighbouring MSOAs (see Methods).

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Data availability

All data used in this study are publicly available. Industrial emissions data are obtained from the United Kingdom Pollutant Release and Transfer Register (UK-PRTR). Neighbourhood-level socioeconomic data, including household income, educational attainment, population, and geographic boundaries, are sourced from the UK Office for National Statistics. The processed datasets generated during the study can be reproduced from these sources using the code described below.

Code availability

All code used to process the data, construct the pollution and socioeconomic indicators, and generate the results and figures reported in this study will be made publicly available upon acceptance.

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Ethics Declaration

The authors declare no competing interests.