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Population Density and Air Pollution: Should Incentives Be the Same Across U.S. Cities and States?

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Abstract. Population concentration generates both economic benefits and environmental costs through agglomeration-related spatial externalities. This paper examines how population density shapes fine particulate matter (PM2.5) concentrations across U.S. states over the period 2000–2023, conceptualizing density as a structural driver of nonlinear environmental externalities within regional systems. Using a panel of all fifty states, I estimate fixed-effects models in which logged PM2.5 is modeled as a flexible quadratic function of logged population density, allowing coefficients to evolve over time and across density regimes.

The results reveal a convex relationship between population density and PM2.5, indicating that the environmental externalities of agglomeration increase at an accelerating rate over much of the density distribution. However, the strength of this nonlinear effect has weakened over time, consistent with regulatory adaptation and technological diffusion. A split-regime analysis further shows that the curvature of the density-pollution relationship differs systematically between low- and high-density states, suggesting heterogeneity in regional externality structures.

These findings contribute to the regional science literature by demonstrating that the environmental consequences of population concentration are nonlinear, heterogeneous, and dynamic within an advanced economy context. More broadly, the results highlight the importance of incorporating spatial externalities and governance scale into density-sensitive regional policy design, particularly in transportation investment, land-use planning, and environmental regulation.

Key words: Population density; PM2.5; Spatial externalities; Agglomeration; Nonlinear effects; Regional heterogeneity

1 Introduction

This paper examines how population density affects PM2.5 concentrations across U.S. states over the period 2000–2023. Specifically, it asks whether the relationship between population density and air pollution is nonlinear, whether it differs across density regimes, and how it evolves over time. Using a panel of all fifty states, I estimate fixed-effects models in which logged PM2.5 is modeled as a quadratic function of logged population density, with coefficients allowed to vary over time. The results reveal a convex relationship, indicating that environmental externalities increase at an accelerating rate with density, although this effect weakens over time and differs across low- and high-density states.

Population concentration is a defining feature of modern economic geography. Agglomeration generates productivity gains through knowledge spillovers, labor-market pooling, infrastructure sharing, and input–output linkages. At the same time, it intensifies congestion, energy consumption, transportation flows, and environmental pressures. These opposing forces imply that population density is not merely a demographic characteristic but a source of spatial externalities whose magnitude and incidence may vary across regional systems. This paper explicitly conceptualizes population density as a structural driver of nonlinear environmental externalities.

Fine particulate matter (PM2.5) provides a particularly relevant lens through which to examine these spatial externalities. Particles small enough ($\leq$ 2.5 micrometers) can penetrate deep into the lungs and enter the bloodstream, increasing the risk of cardiovascular and respiratory disease. Beyond its health effects, PM2.5 also plays an important role in atmospheric dynamics and climate processes (IPCC 2021, WHO 2025).

Despite extensive research, the relationship between population density and PM2.5 remains theoretically ambiguous and empirically unsettled. On one hand, higher density may amplify pollution through congestion and scale effects. On the other hand, density may facilitate cleaner transport, stricter regulation, and technological upgrading.

This paper addresses these issues by focusing on state-level regional systems, which capture both within-region dynamics and broader spatial spillovers under unified policy frameworks. Empirically, I estimate fixed-effects panel models with nonlinear and time-varying specifications and examine heterogeneity across density regimes.

The contribution is threefold. First, the paper conceptualizes population density as a source of nonlinear environmental externalities. Second, it documents heterogeneity across density regimes. Third, it shows that these effects evolve over time.

The remainder of the paper is structured as follows. Section 2 gives literature review. Section 3 describes the data and presents descriptive statistics. Section 4 outlines the empirical methodology and model specifications. Section 5 presents the results, including pooled, regime-specific, and time-varying effects. Section 6 concludes with policy implications and directions for future research.

2 Literature Review

The relationship between urbanization and PM2.5 has been widely studied, but results remain mixed. A global panel study of 135 countries finds that the impact of urbanization depends on development stage (Wang et al. 2019). In Eastern China, PM2.5 exposure declined despite continued urban growth, reflecting regulatory improvements (Zhang et al. 2022). These findings suggest that the density–pollution relationship is context-dependent and evolves over time. Recent global evidence, such as the 2025 IQAir World Air Quality Report (https://www.iqair.com/world-air-quality-report), confirms persistent cross-country variation in PM2.5 levels and highlights ongoing challenges in meeting recommended standards.

City-level evidence further highlights complexity. In Shanghai, density is positively associated with PM2.5 (Han, Sun 2019). Mobility-based studies show unequal exposure across populations (Fan et al. 2022). However, most existing studies are localized and do not fully capture regional spillovers and governance structures.

Two key gaps emerge. First, much of the literature relies on cross-sectional or city-level data, limiting its ability to capture interregional externalities (LeSage, Pace 2009, Kahn, Walsh 2015). Second, many studies assume linear relationships and short time horizons. As a result, nonlinear and dynamic aspects of the density–pollution relationship remain underexplored.

This study contributes by providing a unified panel analysis at the state level, incorporating nonlinearities, temporal dynamics, and regional heterogeneity within a consistent institutional framework.

Table 1: Descriptive Statistics

Variable	Details	Obs	Mean	Median	Std. Dev.	Min	Max
PM2.5	24-hour average concentration of fine particles in the air that are 2.5 micrometers in diameter or smaller, measured in μg/m^3.	1,170	23.6091	22.6667	9.77688	1	151.286
Density	Total population divided by land area in square kilometers	1,170	76.3118	39.15676	101.043	0.42489	492.447
Year		1,170	2011.56	2012	6.927	2000	2023

Notes: PM2.5 data exclude exceptional events such as wildfires and dust storms. A human hair is approximately 70 μm in diameter, compared to ≤ 2.5 μm for PM2.5 particles.

3 Description of Data

3.1 Data Sources

Data on PM2.5 concentrations for the period 2000 to 2023 were obtained from the U.S. Environmental Protection Agency (EPA 2025). For each year, I downloaded individual CSV files containing 24-hour PM2.5 measurements in micrograms per cubic meter (μg/m^3) from specific monitoring locations. To obtain state-level measurements, I selected the "County" option to aggregate monitoring data. To ensure that our analysis reflects typical air quality conditions, I specifically excluded data corresponding to exceptional events, such as wildfires, dust storms, or other unusual pollution episodes, by selecting the "Exclude exceptional events data" option in the EPA dataset interface. I then calculated the average PM2.5 level for each U.S. state and subsequently merged these state-level averages into a single dataset.

Population density (people per square kilometer) was calculated using population and land area data. Population figures were obtained from the Tauberer (2025) GitHub repository, based on U.S. Census Bureau estimates compiled by the Federal Reserve Bank of St. Louis for 1900–2024. State land area data were retrieved from the U.S. Census Bureau.

3.2 Descriptive Statistics

Table 1 presents summary statistics for the main variables used in the analysis, covering 1,170 observations across the 50 U.S. states from 2000 to 2023. The dependent variable, PM2.5, represents the 24-hour average concentration of fine particulate matter (particles with a diameter of $\leq 2.5\mu$m, compared to about 70 μm for a human hair), measured in micrograms per cubic meter (μg/m^3). The mean PM2.5 concentration is 23.61 μg/m^3 and the median is 22.67 μg/m^3, suggesting a slightly right-skewed distribution. Dispersion is substantial, with a standard deviation of 9.78 μg/m^3 and values ranging from 1 μg/m^3 to 151.29 μg/m^3. These figures reflect typical state-level variation over time, after excluding exceptional events such as wildfires and dust storms. The highest average PM2.5 concentration was observed in Oregon in 2020, while the lowest was recorded in South Dakota in 2015. Under normal conditions, this variation likely reflects differences in population density, industrial activity, transportation intensity, and local meteorological conditions.

To formally assess how observed concentrations compare with the commonly recommended benchmark of 15 μg/m^3, Table 2 reports the results of two complementary statistical tests. Panel A presents a one-sample t-test of whether the mean PM2.5 concentration equals 15 μg/m^3. The null hypothesis of equality is strongly rejected ($t = \frac{23.60914-15}{9.776881/\sqrt{1{,}170}} \approx 30.12$, $p < 0.001$), indicating that average PM2.5 concentrations in the sample are statistically significantly higher than the benchmark. Panel B reports a one-sample Wilcoxon signed-rank test for the median. The null hypothesis that the median equals 15 μg/m^3 is also strongly rejected ($z = 24.90$, $p < 0.001$). Consistent with

Table 2: Tests of PM2.5 Levels Against the WHO Benchmark (15 μg/m^3)

Panel A: One-sample t-test (Mean)

Variable	Obs.	Mean	Std. Dev	Std. Err	t-statistic	95% CI	p-value
PM2.5	1,170	23.6091	9.77688	0.28583	30.12	[23.05, 24.17]	< 0.001
Reject H0 (Mean=15 μg/m^3)							

Panel B: Wilcoxon Signed-Rank Test (Median)

positive	Negative	Zero	z-statistics	p-value
1,009	151	10	24.90	< 0.001
Reject H0 (Median=15 μg/m^3)				

this result, 1,009 out of the 1,170 observations exceed the benchmark level, confirming that both the mean and the median PM2.5 concentrations in the sample lie significantly above the recommended threshold.

Table 1 also reports descriptive statistics for population density, defined as total population divided by land area in square kilometers. Population density exhibits a highly skewed distribution: the mean is 76.31 people per km^2, while the median is only 39.16 people per km^2, reflecting the influence of a few very densely populated states. The standard deviation of 101.04 further illustrates the substantial variation across states, with values ranging from 0.42 to 492.45 people per km^2. This range highlights the stark contrast between sparsely populated states such as Alaska and highly urbanized states such as New Jersey. In 2023, New Jersey was the most densely populated state (492.45 people per km^2), whereas Alaska was the least densely populated in 2000 (0.42 people per km^2).

Finally, Table 1 shows that the Year variable ranges from 2000 to 2023, with a mean of 2011.56 and a median of 2012. The relatively low standard deviation of 6.93 reflects the time coverage of the panel.

Overall, the descriptive evidence points to considerable heterogeneity in both PM2.5 levels and population density across states and over time. This heterogeneity motivates the use of a quadratic specification to capture potential nonlinear effects of density on PM2.5, as high-density states may experience different pollution dynamics than low-density states. In addition, the panel structure of the data, with repeated observations for each state over multiple years, justifies the use of fixed-effects regression models to control for time-invariant unobserved heterogeneity across states while estimating the effects of population density and its interactions over time.

4 Methodology

4.1 Model specification: Pooled Sample

I model the natural logarithm of 24-hour PM2.5 [$y_{it} = \ln(\text{PM2.5}_{it})$] as a flexible quadratic function of the natural logarithm of population density [$x_{it} = \ln(\text{Density}_{it})$], allowing curvature, slope, and intercept to vary over time. The log-log transformation allows coefficients to be interpreted as elasticities (e.g., Wooldridge 2009) and the quadratic form captures potential nonlinear effects of population density on PM2.5. The sample includes all 50 U.S. states ($i = 1, \dots, 50$) for the years 2000–2023 ($t = 2000, \dots, 2023$). For clarity, Table 3 summarizes the notation used in the empirical model.

Table 3: Definitions of Variables

Symbol	Definition
ln(PM2.5)	Log pollution
ln(Density)	Log population density
t	Time index (years)
τ_t	year-2000
FE	State fixed effects (time-invariant heterogeneity)

To capture time variation, I define a time variable τ_t = (year-2000), so that the intercept corresponds to the base year 2000. This improves the interpretability of the intercepts and reduces multicollinearity among time-related terms. Without centering, the intercepts would correspond to the expected level of PM2.5 in the non-existent year zero (Ramanathan 2002, p. 147-148, Hoaglin 2016a,b)[1]. Coefficients of the quadratic, linear, and intercept terms are allowed to evolve linearly with time, while the error term captures unobserved variation in PM2.5.

I estimate a time-varying interaction model, where the final specification is given by:

$$\begin{aligned}\ln(\text{PM2.5}) = {} & a_{11}[\ln(\text{Density})]^2 + a_{12}[\text{year} - 2000] * [\ln(\text{Density})]^2 + \\ & + b_{11}\ln(\text{Density}) + b_{12}[\text{year} - 2000] * \ln(\text{Density}) + c_{11} + \\ & + c_{12}[\text{year} - 2000] + \mu_1 \end{aligned} \tag{1}$$

where $a_{11}, a_{12}, b_{11}, b_{12}, c_{11}, c_{12}$ are parameters to be estimated and μ_1 is the error term. This specification allows both the linear and nonlinear effects of population density on PM2.5 to vary over time. In particular, the interaction terms with (year-2000) capture how the slope and curvature of the relationship evolve throughout the sample period. For completeness, the full derivation and alternative parameterizations are provided in Appendix A.1.

To clarify the interpretation of the interaction terms, consider the marginal effect of population density on PM2.5. Taking the first derivative with respect to ln(Density), we obtain:

$$\frac{\partial \ln(\text{PM2.5})}{\partial \ln(\text{Density})} = b_{11} + b_{12}[\text{year} - 2000] + 2a_{11}\ln(\text{Density}) + 2a_{12}[\text{year} - 2000]\ln(\text{Density}).$$

This expression shows that the marginal effect of population density on PM2.5 is not constant but depends both on the level of density and on time. In particular, the interaction terms imply that the slope and curvature of the relationship evolve over the sample period, allowing the impact of density to strengthen or weaken over time. More generally, this reflects the role of interaction effects, where the influence of one variable depends on the value of another variable rather than remaining fixed.

4.2 Model specification: Density Regime Split

To examine heterogeneity in the density–pollution relationship, I extend the baseline specification by allowing the effects of population density to differ across density regimes. Specifically, the sample is divided into below- and above-median density states, and a regime indicator (D_{AD}) is introduced to capture these differences. D_{AD} is 1 when the density is above the median and 0 otherwise.

The empirical model retains the quadratic specification in log population density while allowing the intercept, slope, and curvature to vary both across density regimes and over time. This flexible formulation enables the marginal effect of density on PM2.5 to differ systematically between low- and high-density states, while also evolving throughout the sample period.

Formally, the model is specified as:

[1] Hoaglin (2016a) emphasizes that reusing the same letters in models with different sets of predictors can obscure the individual contribution of each predictor to the coefficients. For instance, if the model $2x + 5t$ fits the data on y well, then the model $[-3x + 5(t + x)]$ will fit the data equally well, since both produce identical predicted values (p. 7).

$$
\begin{aligned}
\ln(\text{PM2.5}) = {} & a_{21}[\ln(\text{Density})]^2 + a_{22}D_{\text{AD}} * [\ln(\text{Density})]^2 + \\
& + a_{23}[\text{year} - 2000] * [\ln(\text{Density})]^2 + \\
& + a_{24}D_{\text{AD}} * [\text{year} - 2000] * [\ln(\text{Density})]^2 + \\
& + b_{21}\ln(\text{Density}) + b_{22}D_{\text{AD}} * \ln(\text{Density}) + \\
& + b_{23}[\text{year} - 2000] * \ln(\text{Density}) + \\
& + b_{24}D_{\text{AD}} * [\text{year} - 2000] * \ln(\text{Density}) + c_{21} + \\
& + c_{22}D_{\text{AD}} + c_{23}[\text{year} - 2000] + \\
& + c_{24}D_{\text{AD}} * [\text{year} - 2000] + \mu_2
\end{aligned}
$$

where $a_{21}, \cdots, a_{24}, b_{21}, \cdots, b_{24}, c_{21}, \cdots, c_{24}$ are parameters to be estimated and μ_2 is the error term. The coefficients are allowed to vary by regime and time, and the error term captures unobserved variation in PM2.5 not explained by density, regime classification, or time dynamics.

This specification implies that both the level and the shape of the density–pollution relationship may differ across regimes. In particular, it allows the marginal effect of population density – and the location of potential turning points – to vary between low- and high-density states. For completeness, the full expansion of the model and the derivation of marginal effects are provided in Appendix A.2.

The marginal effect of population density is given by:

$$
\begin{aligned}
\frac{\partial \ln(\text{PM2.5})}{\partial \ln(\text{Density})} = {} & b_{21} + b_{22}D_{\text{AD}} + b_{23}[\text{year} - 2000] + b_{24}D_{\text{AD}}[\text{year} - 2000] + \\
+2\Big(a_{21} + a_{22}D_{\text{AD}} + a_{23}[\text{year} - 2000] + a_{24}D_{\text{AD}}[\text{year} - 2000]\Big) * \ln(\text{Density})
\end{aligned}
$$

This expression shows that the marginal effect of density depends on both time and the density regime.

I estimate our models using fixed-effects regressions to account for time-invariant differences across states. Formally, for a single explanatory variable x_{it}, the fixed-effects (within) transformation is $y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + (u_{it} - \bar{u}_i)$, where $\bar{y}_i$ and $\bar{x}_i$ are state-specific averages over time (Wooldridge 2009, p. 481-482). This approach can be generalized to multiple predictors, allowing consistent estimation of linear and quadratic terms, as well as interactions, while controlling for unobserved, time-invariant heterogeneity.

5 Results

Table 4 presents the fixed-effects regression estimates of the relationship between population density and PM2.5 concentrations for the 50 U.S. states over the period 2000–2023. The dependent variable in all specifications is the natural logarithm of 24-hour average PM2.5 concentrations.

5.1 Baseline Density Effects and Time Trends

Across all three specifications in Table 4, the coefficient on the time trend (year-2000) is negative and statistically significant at the 1% level, indicating a systematic decline in PM2.5 concentrations over time, holding other factors constant. In column (2), for example, the estimated coefficient of -0.0234 implies an average annual reduction of approximately 2.3%, which is consistent with long-run improvements in air quality driven by tighter environmental regulation and technological progress.

In column (1), which includes both linear and quadratic terms in log population density and their interactions with time, neither the linear density term nor the quadratic term is statistically significant. This suggests that, once state fixed effects and time dynamics are controlled for, the relationship between population density and PM2.5 is not well captured by a static quadratic specification.

Table 4: Fixed-Effects Estimates of PM2.5 and Population Density (2000–2023), Including Nonlinear Effects

Variables	(1) fixed-effect ln(PM2.5)	(2) fixed-effect ln(PM2.5)	(3) fixed-effect ln(PM2.5)
$\ln(\text{Density})^2$	0.0846	-	0.0991***
	(0.116)	-	(0.0373)
$(\text{year-2000})*\ln(\text{Density})^2$	-0.000378	-	-0.00104***
	(0.000499)	-	(0.000153)
ln(Density)	0.225	0.820***	-
	(0.816)	(0.269)	-
(year-2000)*ln(Density)	-0.00437	-0.00555***	-
	(0.00402)	(0.00105)	-
Constant	1.500	0.626	2.076***
	(1.398)	(0.933)	(0.522)
(year-2000)	-0.0186**	-0.0203***	-0.0234***
	(0.00931)	(0.00496)	(0.00300)
Observations	1,170	1,170	1,170
R-squared	0.369	0.368	0.368
F(5,1115)	130.46***	-	-
F(3,1117)	-	217.08***	-
F(3,1117)	-	-	216.65***
Number of States	50	50	50

Notes: Numbers in parentheses are standard errors. ***p<0.01

When the model is simplified in column (3) to highlight the nonlinear effect of density, a clearer pattern emerges. The coefficient on the squared log-density term, $[\ln(\text{Density})]^2$, is positive and highly significant (0.0991, $p < 0.01$), indicating that the marginal effect of population density on PM2.5 increases at an accelerating rate. This implies a convex relationship between density and pollution.

The estimated convex curve begins at the point $[\ln(1), 2.076] = [0, 2.076]$, corresponding to the model's constant term and representing the predicted log PM2.5 concentration in the year 2000 when $\ln(\text{Density}) = 0$ (i.e., density = 1 person per square kilometer). On the original scale, this corresponds to a predicted concentration of $\exp(2.076) \approx 7.97\mu$g, which is below the WHO 24-hour benchmark of 15 μg/m^3. According to the estimates, this benchmark is reached in the year 2000 at a population density of approximately 12.5 persons per square kilometer (see Appendix A.3 for the detailed calculation).

The interaction term between squared log-density and time is negative and statistically significant (-0.00104, $p < 0.01$), indicating that the strength of this nonlinear effect has weakened over time. Overall, these results suggest that although densely populated states historically experienced disproportionately higher PM2.5 concentrations, the environmental penalty associated with very high density has gradually declined, likely reflecting the effects of stricter regulation and cleaner production technologies.

5.2 Time-Varying Density Effects

Columns (1) and (2) further allow for the effect of population density to vary over time through interactions with the time trend. In column (2), the interaction between $\text{year} - 2000$ and $[\ln(\text{Density})]^2$ is negative and statistically significant, indicating that the curvature of the density–pollution relation has flattened over the sample period.

Although high-density states continue to exhibit higher PM2.5 concentrations on average, the gap between low- and high-density states has narrowed over time. This convergence suggests that technological improvements and regulatory interventions may have been adopted earlier or more intensively in denser states, where political pressure and exposure to pollution tend to be stronger.

Taken together, these results provide evidence that the impact of population density on air quality is not only nonlinear, but also time-varying. The environmental cost of urban density, while still present, has become less steep over time, reflecting broader structural changes in pollution control and production technologies.

5.3 Split-Regime Sample: Low- versus High-Density States

To examine whether the relationship between population density and PM2.5 differs across density regimes, the sample is divided at the median population density. Separate effects are then estimated for states below and above this threshold. Table 5 presents the results using both fixed-effects and stepwise specifications.

Table 5: Nonlinear and Threshold Effects of Population Density on PM2.5 (2000–2023)

Variables	(1) Fixed-effect ln(PM2.5)	(2) Stepwise ln(PM2.5)
$\ln(\text{Density})^2$	0.567**	0.0518***
	(0.245)	(0.0112)
D_{AD} * $\ln(\text{Density})^2$	-0.405	-0.0419***
	(0.482)	(0.0113)
(year-2000) * $\ln(\text{Density})^2$	-0.00192	-0.000939***
	(0.00154)	(0.000174)
D_{AD} * (year-2000) * $\ln(\text{Density})^2$	-0.000164	
	(0.00473)	
ln(Density)	-2.185	-0.133***
	(1.335)	(0.0419)
D_{AD} * ln(Density)	1.279	0.136***
	(3.974)	(0.0391)
(year-2000) * ln(Density)	-0.00632	
	(0.00640)	
D_{AD} * (year-2000) * ln(Density)	0.0196	
	(0.0453)	
Constant	4.128**	3.339***
	(1.810)	(0.0550)
D_{AD}	0.719	
	(8.440)	
(year-2000)	-0.000189	-0.0211***
	(0.0124)	(0.00299)
D_{AD} * (year-2000)	-0.0607	
	(0.111)	
Observations	1,170	1,170
R-squared	0.373	0.307
F(11,1109)	59.88***	
F(6, 1163)		85.79***
Number of States	50	50

Notes: Numbers in parentheses are standard errors. ***p<0.01

In both models, the quadratic term in log population density is positive and statistically significant for low-density states. This indicates that even among less densely populated states, PM2.5 concentrations increase at an accelerating rate as density rises. In high-density states, the interaction term $D_{\text{AD}} \times [\ln(\text{Density})]^2$ is negative and significant in the stepwise model, implying that the rate at which pollution increases with density is lower in these states compared with low-density states. In other words, the marginal environmental cost of additional density diminishes at very high population densities.

The interactions with time reveal a gradual flattening of the density–pollution relationship over the period 2000–2023. The coefficient on $[\text{year} - 2000] \times [\ln(\text{Density})]^2$ is negative and statistically significant, indicating that nonlinear effects have weakened over time. While this decline is observed in both regimes, it is slightly smaller in high-density states, suggesting slower convergence in extremely dense environments.

Overall, the split-regime analysis confirms that the density–pollution relationship is both nonlinear and heterogeneous. While a convex pattern is evident in both groups, it is stronger among low-density states and is gradually converging over time. The implications of these differences for predicted pollution levels are illustrated in Figure 2, discussed in Section 5.5.

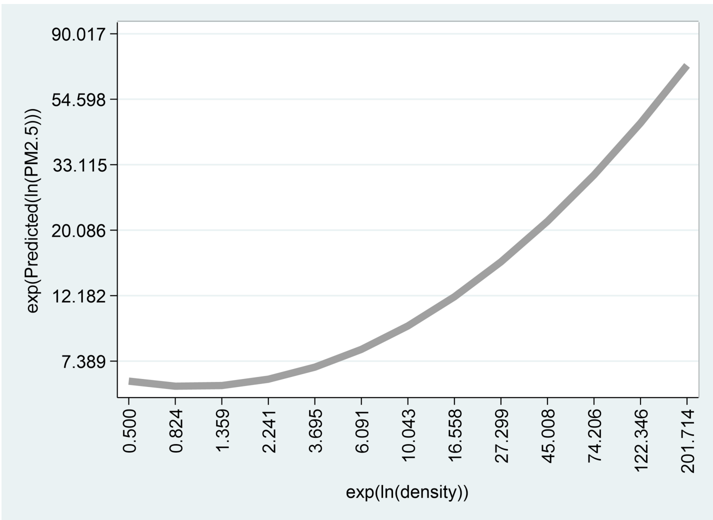
5.4 Goodness of Fit

All models explain a similar proportion of within-state variation in logged PM2.5 concentrations, with $\mathbf{R^2}$ values around 0.307–0.373. The F-statistics are large and highly significant, confirming that the models jointly explain a substantial share of variation in air pollution levels over time within states.

5.5 Visualization of Nonlinear Effects

Figure 1 illustrates the convex relationship between population density and predicted PM2.5 concentrations based on column (3) of Table 4. Predicted values are exponentiated to improve interpretability in micrograms per cubic meter. At low to moderate population densities, predicted PM2.5 levels increase gradually, while at higher densities the increase becomes more pronounced, reflecting the positive and significant quadratic term.

Figure 2 presents the heterogeneous effects across low- and high-density regimes based on the stepwise estimates in column (2) of Table 5. The predictions are computed for the mean year of the sample, 2011, and displayed on the original PM2.5 scale. The WHO 24-hour benchmark of 15 μg/m^3 is included as a reference line.

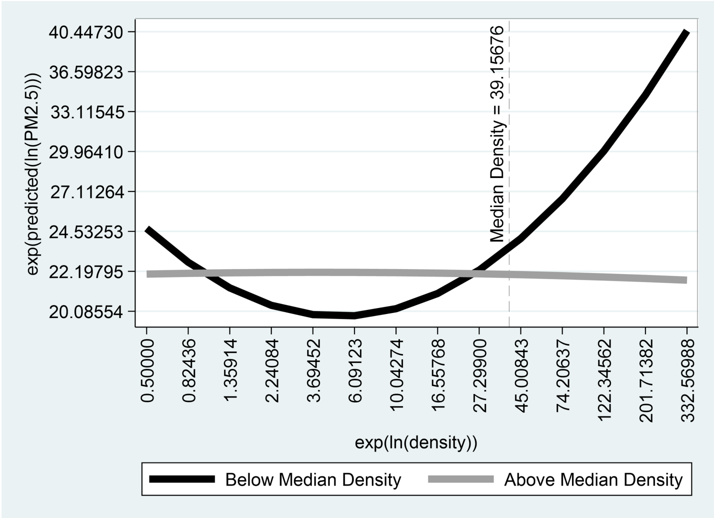


Notes: Based on column (3) of Table 4. The horizontal axis represents population density per square kilometer, and the vertical axis represents the projected level of 24-hour PM2.5 in μg/m^3. According to WHO (2021), the 24-hours recommended PM2.5 level is up to 15 μg/m^3.

Figure 1: Quadratic Effect of Density on Predicted PM2.5 Levels (Exponentiated Scale)

Across the entire density distribution, predicted PM2.5 concentrations remain above the WHO benchmark. The curve reaches its minimum at approximately 20 μg/m^3, indicating that even at the most favorable point of the distribution, predicted pollution levels exceed recommended exposure limits. In the low-density regime, PM2.5 concentrations increase sharply with rising population density, reflecting the strong nonlinear effect estimated in Table 5. In the high-density regime, predicted concentrations are higher overall, but the slope of the curve becomes flatter at very high densities. This suggests that further increases in density at already high levels have a smaller marginal effect on pollution.

These results highlight that, even at the midpoint of the sample period, population density is associated with systematically elevated PM2.5 concentrations across both regimes. The fact that the minimum predicted value exceeds the WHO benchmark underscores the persistence of air quality challenges in both low- and high-density environments, despite overall improvements over time.



Notes: Based on column (2) of Table 5. The horizontal axis represents population density per square kilometer, and the vertical axis represents the projected level of 24-hour PM2.5 in μg/m^3. According to WHO (2021), the 24-hours recommended PM2.5 level is up to 15 μg/m^3.

Figure 2: Heterogeneous Effects of Population Density on Predicted PM2.5 Levels

5.6 Summary of Main Findings

PM2.5 concentrations have declined significantly across U.S. states over time. Population density exhibits a convex relationship with PM2.5, with pollution increasing disproportionately at higher densities, although this effect has weakened, indicating convergence between high- and low-density states. The split-regime analysis shows that the convex pattern is stronger in low-density states, while in high-density states, additional increases in population have a smaller marginal effect. Despite improvements, predicted PM2.5 levels remain above the WHO benchmark for the entire density distribution. These results highlight the importance of accounting for nonlinear and time-varying effects when evaluating the environmental consequences of population density and urbanization.

6 Summary and Conclusions

This study examines how population density shapes PM2.5 concentrations across U.S. states from 2000 to 2023 using EPA monitoring data that exclude exceptional events and population measures based on Census Bureau estimates. The descriptive analysis shows that PM2.5 levels are consistently above the commonly used 15 μg/m^3 benchmark in most states, while population density varies sharply—from extremely sparse regions to highly urbanized areas. Fixed-effects regressions reveal a nonlinear, convex relationship between density and pollution, with the marginal effect of density rising at an accelerating rate. However, this nonlinear effect has weakened over time, indicating convergence between low- and high-density states. A split-regime analysis confirms that density increases pollution more steeply in low-density states, while high-density states exhibit a flatter marginal profile, likely due to earlier regulatory action and technology adoption. Despite steady improvements, predicted PM2.5 levels remain above the WHO benchmark across the entire density range. These improvements are likely associated with specific policy and technological changes, including stricter emissions standards, the expansion of public transportation systems, and increased electrification. In addition, behavioral factors such as rising environmental awareness may have contributed to the observed improvements in air quality.

An important consideration in interpreting these results is the role of regulatory heterogeneity and spatial spillovers. Environmental regulation and enforcement vary across states, and while fixed effects control for time-invariant differences, time-varying policy changes may contribute to the observed convergence in PM2.5 levels. In addition, PM2.5

can travel across state boundaries through atmospheric transport. Therefore, the estimated relationships capture both local emissions and interregional spillovers, consistent with spatial externalities.

The broader significance of PM2.5 extends beyond public health. Fine particles exert both warming and cooling climate effects: components such as black carbon absorb sunlight, darken snow surfaces, and warm the lower atmosphere, while sulfates and organic aerosols scatter sunlight and influence cloud properties, thereby exerting cooling effects (Climate Change Academy 2025). Aerosols also shape global biogeochemical cycles. Mineral dust, marine aerosols, and anthropogenic particles deliver iron, phosphorus, and other nutrients to terrestrial and ocean ecosystems, stimulating primary productivity and affecting carbon uptake (Ito et al. 2023, Hird et al. 2024). Ocean–atmosphere feedbacks further link aerosol chemistry to cloud formation and long-term radiative forcing (Sellegri et al. 2024, Mahowald 2011). Because PM2.5 emissions often coincide with fossil-fuel CO_2 emissions, reducing fine particulate pollution – especially black carbon – offers near-term benefits for both climate mitigation and human health.

The findings suggest several priority areas for policy action. Targeted mitigation is especially important in states with low population density, because nonlinear effects are strongest there and even modest increases in population or economic activity can lead to sharp increases in pollution. These regions would benefit from enhanced monitoring, stricter emissions standards for industry and transport, and early adoption of clean technologies. Stronger controls are also needed in highly populated environments. Although the marginal effects of density are flatter in these areas, overall pollution levels remain high, which makes the expansion of public transportation, faster progress on electrification, the development of green infrastructure in cities, and firm enforcement of industrial standards particularly important.

A further policy consideration concerns relocation incentives. In practice, many governments already offer incentives and subsidies that encourage relocation to specific areas. Incorporating environmental criteria into these programs could be especially valuable. The state may increasingly prioritize relocation toward regions with lower environmental impact or reduced air pollution rather than toward areas that experience substantial environmental stress. Such policies could serve as a complementary tool for safeguarding air quality, reducing the long-term burden of particulate emissions, and supporting broader climate goals, including reducing ozone-related harm and fostering a more sustainable spatial distribution of population and economic activity.

It is also essential to integrate air-quality policy with climate policy. Reductions in PM2.5 and in emissions that contribute to climate change, especially black carbon, offer substantial shared benefits, so federal and state governments should coordinate strategies that address both challenges simultaneously. Improving monitoring and harmonizing data remains a key priority as well. Continued refinement of emissions inventories, expansion of monitoring networks, and the inclusion of aerosol–climate interactions in urban planning will strengthen the reliability of future assessments.

The manuscript has several notable strengths. It draws on a long panel that covers all fifty states over a period of twenty-four years, and it employs fixed-effects models that account for unobserved characteristics specific to each state. The study also identifies nonlinear and time-varying relationships that earlier work has often overlooked, and it effectively links its empirical results to the broader literature on aerosols and climate. At the same time, the analysis has important limitations. It does not include several potentially influential covariates, such as industry composition, patterns of energy use, and meteorological conditions, all of which may shape the relationship between population density and pollution. The functional form is restricted to a quadratic specification, even though more flexible approaches, such as splines or machine learning, could reveal additional nonlinearities. Aggregating data at the state level also conceals substantial variation within states, particularly in metropolitan areas where exposure patterns can differ sharply. Finally, although the manuscript discusses interactions between climate and aerosols, it does so at a conceptual level and does not incorporate these processes directly into the empirical model.

Overall, the findings highlight that while U.S. air quality has improved substantially, population density remains a central determinant of PM2.5 levels, and pollution remains above recommended thresholds across the full density distribution. Given the dual public-health and climate implications of fine particulate matter, effective policy must combine targeted local interventions, environmentally informed relocation and incentive strategies, and integrated national approaches that reduce fossil-fuel reliance and curb PM2.5 emissions in both low- and high-density environments.

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A Appendix:

A.1 Full Model Derivation and Time-Varying Parameterization

Formally, the model is:

$$y_{it} = A_1(\tau_t)x_{it}^2 + B_1(\tau_t)x_{it} + C_1(\tau_t) + \varepsilon_{1,it}$$

where

$$\begin{aligned} A_1(\tau_t) &= a_{11} + a_{12}\tau_t, \\ B_1(\tau_t) &= b_{11} + b_{12}\tau_t, \\ C_1(\tau_t) &= c_{11} + c_{12}\tau_t, \end{aligned} \tag{2}$$

and $\varepsilon_{1,it}$ – is the random disturbance term.
Substituting these expressions into equation (1) gives the expanded form:

$$y_{it} = a_{11}x_{it}^2 + a_{12}\tau_t x_{it}^2 + b_{11}x_{it} + b_{12}\tau_t x_{it} + c_{11} + c_{12}\tau_t + \varepsilon_{1,it}$$

or, equivalently, written in a more intuitive notation (indices omitted for convenience):

$$\begin{aligned} \ln(\text{PM2.5}) = a_{11}[\ln(\text{Density})]^2 &+ a_{12}[\text{year} - 2000] * [\ln(\text{Density})]^2 + \\ &+ b_{11}\ln(\text{Density}) + b_{12}[\text{year} - 2000] * \ln(\text{Density}) + \\ &+ c_{11} + c_{12}[\text{year} - 2000] + \mu_1 \end{aligned}$$

Here, μ_1 is the error term, capturing unobserved variation in PM2.5 not explained by density or time trends.

A.2 Density-Regime Model

Formally, the density-regime model is:

$$\ln(\text{PM2.5}) = A_t[\ln(\text{Density})]^2 + B_t \ln(\text{Density}) + C_t + \mu_2$$

where the coefficients vary by time and density regime:

$$\begin{aligned}
A_t &= a_{21} + a_{22}[\text{year} - 2000] + a_{23}D_{\text{AD}} + a_{24}D_{\text{AD}} * [\text{year} - 2000] \\
B_t &= b_{21} + b_{22}[\text{year} - 2000] + b_{23}D_{\text{AD}} + b_{24}D_{\text{AD}} * [\text{year} - 2000] \\
C_t &= c_{21} + c_{22}[\text{year} - 2000] + c_{23}D_{\text{AD}} + c_{24}D_{\text{AD}} * [\text{year} - 2000]
\end{aligned}$$

where $D_{\text{AD}} = 1$ for above-median density states and $D_{\text{AD}} = 0$ otherwise. Substituting these expressions into the baseline equation gives the full interaction model:

$$\begin{aligned}
&\ln(\text{PM2.5}) = \\
&\qquad [a_{21} + a_{22}[\text{year} - 2000] + a_{23}D_{\text{AD}} + a_{24}D_{\text{AD}} * [\text{year} - 2000]][\ln(\text{Density})]^2 + \\
&\qquad + [b_{21} + b_{22}[\text{year} - 2000] + b_{23}D_{\text{AD}} + b_{24}D_{\text{AD}} * [\text{year} - 2000]] \ln(\text{Density}) + \\
&\qquad + [c_{21} + c_{22}[\text{year} - 2000] + c_{23}D_{\text{AD}} + c_{24}D_{\text{AD}} * [\text{year} - 2000]] + \mu_2
\end{aligned}$$

A.3 Calculation of Population Density Corresponding to the PM2.5 Benchmark

Using the estimates from column (3) of the main model, I can calculate the population density at which the PM2.5 benchmark of 15 $\mu\text{g/m}^3$ is reached in the year 2000. The model specification in 2000 is:

$$\ln(\text{PM2.5}) = \text{Constant} + \beta[\ln(\text{Density})]^2$$

From column (3) we know that Constant = 2.076, and β (for $[\ln(\text{Density})]^2$) = 0.0991 Setting PM2.5 to the benchmark value of 15 $\mu\text{g/m}^3$, we have:

$$\begin{aligned}
\ln(15) &= 2.076 + 0.0991 \cdot [\ln(\text{Density})]^2 \\
2.708 &= 2.076 + 0.0991 \cdot [\ln(\text{Density})]^2 \\
[\ln(\text{Density})]^2 &= \frac{2.708 - 2.076}{0.0991} \approx 6.376 \\
\ln(\text{Density}) &= \sqrt{6.376} \approx 2.525 \\
\text{Density} &= e^{2.525} \approx 12.5 \text{ people per square kilometer}
\end{aligned}$$

Thus, in the year 2000, a population density of approximately 12.5 people per square kilometer corresponds to a PM2.5 concentration of 15 $\mu\text{g/m}^3$ according to the estimated model.