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# Air Quality and Urban Form in U.S. Urban Areas: Evidence from Regulatory Monitors

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**S** Supporting Information

ABSTRACT: The layout of an urban area can impact air pollution via changes in emissions and their spatial distribution. Here, we explore relationships between air quality and urban form based on cross-sectional observations for 111 U.S. urban areas. We employ stepwise linear regression to quantify how long-term population-weighted outdoor concentrations of ozone, fine particulate matter  $(PM_{2.5})$ , and other criteria pollutants measured by the U.S. Environmental Protection Agency depend on urban form, climate, transportation, city size, income, and region. Aspects of urban form evaluated here include city shape, road density, jobs-housing imbalance,



population density, and population centrality. We find that population density is associated with higher population-weighted PM<sub>2.5</sub> concentrations ( $p < 0.01$ ); population centrality is associated with lower population-weighted ozone and PM<sub>2.5</sub> concentrations  $(p < 0.01)$ ; and transit supply is associated with lower population-weighted PM<sub>2.5</sub> concentrations  $(p < 0.1)$ . Among pollutants, interquartile range changes in urban form variables are associated with 4%-12% changes in population-weighted concentrations—amounts comparable, for example, to changes in climatic factors. Our empirical findings are consistent with prior modeling research and suggest that urban form could potentially play a modest but important role in achieving (or not achieving) long-term air quality goals.

## 1. INTRODUCTION

We explore here the relationship between air quality and attributes of urban form, using cross-sectional observations for U.S. urban areas. Our investigation is motivated in part by increasing interest in urban planning strategies to improve air quality (e.g., "Smart Growth"; Centers for Disease Control and Prevention recommendations<sup>1</sup>) but with limited observational evidence linking urban form and air quality at a multiurban scale.

Urban design likely influences air quality directly and indirectly through travel behavior, land cover, and spatial distributions of land use. Since transportation is a major source of air pollution emissions<sup>2</sup> in the U.S., the impact of urban form on travel behavior (via, e.g., vehicle kilometers traveled (VKT), mode share, and trip length) may influence air quality. Research suggests that population density, transit supply, and "traditional" (e.g., gridded) street networks are negatively associated with VKT and positively associated with<br>alternative modes (transit, walking, biking).<sup>3–6</sup> Other reported links between urban form and air quality include the following: impervious land cover increases photochemical ozone formation through the urban heat island effect;<sup>7,8</sup> configurations of streets and buildings influence pollutant dispersion ("urban street-canyon effect");<sup>9</sup> and spatial distributions of land uses  $(e.g.,)$  housing, employment) relative to pollution influence exposures.

Our analysis covers all of the EPA's criteria pollutants (presented in the Supporting Information [SI]) but focuses here

on ozone and fine particulate matter  $(PM<sub>2.5</sub>)$  because of their widespread health impacts. Both pollutants are associated with cardiovascular and respiratory morbidity and mortality.<sup>11-13</sup> Approximately 40% of U.S. population lives in a county that violates National Ambient Air Quality Standards (NAAQS) for ozone,  $PM_{2.5}$ , or both.<sup>2</sup> Given projected increases in U.S. urban populations  $(+100$  million by 2050),<sup>14</sup> policies would ideally aim to accommodate urban growth while improving air quality.

Extant modeling studies suggest that, relative to baseline or high-density ("compact growth") scenarios, low-density ("urban sprawl") scenarios may yield higher ambient concentrations but comparable or lower average exposures.<sup>15-17</sup> Factors influencing these relationships include neighborhood-scale urban design (i.e., building density and layout, street canyons),<sup>18,19</sup> the magnitude of emission reductions achieved via increasing density, $2^{0}$  regional land cover-surface meteorology interactions, $21$  and the relative tradeoff between exposures for urban-core versus urban-periphery residents.

To our knowledge, only four publications<sup>22–25</sup> explore these topics empirically. Bechle et al. $^{22}$  used satellite-derived estimates of urban form and  $NO<sub>2</sub>$  air pollution for 83 global cities; they







*<sup>a</sup>* Monitor inclusion criteria: (1) observations reported for at least 75% of expected sampling days in the study period and (2) not source-oriented (i.e.,"ambient"). Exclusions: 8 ozone, 132 PM<sub>2.5</sub> monitors failed criterion #1 (only); 5 ozone, 8 PM<sub>2.5</sub> monitors failed criterion #2 (only); 1 ozone, 1 PM<sub>2.5</sub> monitor failed both criteria. <sup>b</sup> Population-weighted concentration for each UA is calculated from the interpolated concentration (using inverse distance-weighting of the long-term average concentrations from the 3 nearest monitors within 50 km) for each 1-km gridcell center within the UA and the estimated population in each 1-km gridcell (see Equation S1 in the Supporting Information). *<sup>c</sup>* Arithmetic Mean (Arithmetic Standard Deviation). *<sup>d</sup>* LAQI<sup>27</sup> is the population-weighted sum of ozone concentration (1990 ozone season average daily 8-h maximum concentration) divided by ozone 8-h EPA standard (75 ppb), plus PM<sub>2.5</sub> concentration (2000 annual average concentration) divided by  $PM_{2.5}$  annual EPA standard (15  $\mu$ g m<sup>-3</sup>).

found that more-contiguous cities (i.e., cities with less leapfrog development) experience lower annual-average  $NO<sub>2</sub>$  concentrations  $(p = 0.01)$ . Ewing et al.<sup>23</sup> reported that residential density (based on the Smart Growth America [SGA] composite density index) is associated with decreased ozone concentrations (annual fourth highest daily maximum 8-h average) in a crosssection of 83 U.S. metropolitan regions ( $p < 0.001$ ). Stone<sup>24</sup> found that in a cross-section of 45 U.S. metropolitan areas, ozone NAAQS exceedences increase with sprawl (based on the SGA sprawl index;  $p < 0.01$ ), after controlling for population, temperature, and precursor emissions. Schweitzer and Zhou,<sup>25</sup> studying 80 U.S. metropolitan areas, reported that peak ozone concentrations are higher for more- than for less-sprawling areas  $(p < 0.05)$ , but ozone and PM<sub>2.5</sub> total peak exposures are lower for more-sprawling regions ( $p < 0.05$ ).

Our main research questions are (1) is measured ambient air pollution in a cross-section of U.S. cities correlated with urban form, after accounting for other common explanatory variables, and (2) if so, at what magnitude? We build on the limited prior measurement-based research by (A) evaluating all EPA criteria pollutants plus a summary metric, (B) employing a more nuanced evaluation of urban form (we consider five urban attributes at the urban area scale; prior U.S.-focused empirical investigations employ composite measures of urban sprawl at the metropolitan statistical area scale) and urban meteorology (e.g., including atmospheric dilution rates), and (C) considering a wider crosssection of U.S. cities. While previous studies have considered NAAQS exceedences or peak concentrations, we focus on longterm average population-weighted concentrations; for some pollutants, epidemiological evidence suggests there may be different, potentially more severe, health outcomes associated with chronic rather than acute exposures.

#### 2. METHODS

We use stepwise linear regression to quantify relationships between urban form and measured population-weighted air pollutant concentrations for a cross-section of 111 U.S. urban areas (UAs). Explanatory variables include measures of urban form, climate, transportation, land area, income, and region. We

analyze eight pollutants (EPA's criteria pollutants: carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter (fine particulate matter  $[PM_{2.5}]$ , coarse particulate matter  $[PM_{10}]$ , and total suspended particulates [TSP]), and sulfur dioxide) plus a summary metric (long-term air quality index [LAQI], defined below). For concision, descriptions below focus on ozone and  $PM_{2.5}$ ; details for the remaining pollutants are in Table S1. Figures S1-S2 provide boxplots for dependent and independent variables.

2.1. Urban Areas. We identified ten available data sets on urban form in the U.S. (Table S2). We selected the Bento et al. $3$ data set based on number of urban form metrics reported (4 metrics: population centrality, road density, jobs-housing imbalance, city shape), spatial scale considered (UAs), and number of cities included (114 U.S. cities). The Bento data are the basis for our sample selection and primary year of analysis (1990). Of the 114 UAs in the Bento data set, we eliminated two population-outliers (New York; Los Angeles) and one incompletedata UA (San Francisco), yielding the 111 UAs evaluated here. These 111 UAs accounted for 38% of U.S. population (59% of U.S. urban population) and 1.2% of U.S. continental land area in 1990.

2.2. Dependent Variables. Dependent variables are populationweighted long-term average concentrations derived from U.S. Environmental Protection Agency (U.S. EPA) Air Quality System daily monitor data.<sup>26</sup> Analyses are based on spatial interpolation of EPA monitors that meet the following inclusion criteria:  $(1)$  located within the UA,  $(2)$  designated as nonsourceoriented (i.e., "ambient"), and (3) reported observations for at least 75% of expected sampling days in the study period. In total, 267 ozone monitors (in 100 of the UAs) and 344  $PM_{2.5}$ monitors (in 107 of the UAs) meet the inclusion criteria. The median (arithmetic mean) number of monitors per UA for the sample of 111 UAs is 2 (2.4) for ozone and 2 (3.1) for  $PM_{2.5}$ . For ozone, 11 UAs (10%) have 0 monitors, 41 (37%) 1 monitor, 45 (41%) 2 to 4 monitors, 14 (13%) 5 or more monitors. For  $PM_{2.5}$ , 4 (4%) have 0 monitors, 25 (23%) 1 monitor, 59 (53%) 2 to 4 monitors, 23 (21%) 5 or more monitors. Table 1 describes the EPA monitor data included in the study. Figure S3 maps the UAs and the associated number of monitors.

#### Table 2. Description of Explanatory Variables



For each included monitor, we calculated the long-term arithmetic average of daily (24-h) summary data, except for ozone, where we calculated the 5-month summer (i.e., ozone season) average of daytime  $(10:00-18:00)$  concentrations. We consider daytime-only concentrations for ozone to control for the effect of NO*<sup>x</sup>* titration at night. (Table S3 presents results for two alternate ozone metrics: nighttime-only and 24-h concentrations.) For  $PM_{2.5}$  only, we use year-2000 instead of year-1990 measurements.  $PM_{2.5}$  monitors were not widespread in 1990; we selected year-2000 as the first year of EPA regulation and nation-wide daily sampling of  $PM_{2.5}$  and supplemented our data set with an alternative PM metric widely recorded in 1990: total suspended particulates (TSP). In addition to the individual pollutants, we assess the influence of urban form on an aggregate measure of air pollution using the long-term air quality index (LAQI; Table 1).<sup>27</sup> For comparison, we also generated a year-2000 ozone model; results are consistent with the year-1990 ozone model (see SI) and so are omitted here.

Our comparison metric for each UA is the long-term population-weighted concentration, calculated using inverse distanceweighted interpolation of the three nearest monitors within 50  $km^{28}$  and population density on a 1-km grid (year-1990).<sup>29</sup> We employ population-weighting within each UA to obtain a spatial average that incorporates within-urban spatial variations in concentrations and population.

2.3. Independent Variables. Independent variables in the model include five urban form metrics, plus measures of climate, transportation infrastructure, land area, income, and region (Table 2).

2.3.1. Urban Form. Bento et al.<sup>3</sup> provide four urban form metrics per UA (population centrality, road density, jobs-housing imbalance, city shape [a measure of circularity]; see Table 2). Using year-1990 Census data, we added average population density as a fifth metric.

2.3.2. Climate. Climate influences pollution formation and dispersion.<sup>30</sup> To account for differences in climate across UAs, we include in the model temperature and dilution rate for time periods matching the air pollution data. Temperature data are from the National Climatic Data Center.<sup>31</sup> We tested multiple temperature metrics (see SI) in preliminary regressions, and then in the final models employed the metric with highest predictive power for each pollutant: 5-month summer average daily maximum temperature (ozone) and annual heating degree days (HDD;  $PM<sub>2.5</sub>$ ). We calculate dilution rate (product of mixing height and wind speed averaged over the mixing height) from National Aeronautics and Space Administration (GMAO/MERRA) hourly data, interpolated to 0.1 h on a 1-km grid in each  $\mathrm{UA}^{32}$  We use a power law to calculate average wind speed from the surface to the top of the

# Table 3. Standardized Coefficients<sup>a</sup> for Stepwise Linear Regression Models



*<sup>a</sup>*Coefficient standardized to interquartile ranges (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted air pollution concentration). <sup>*b*</sup> Population-weighted year-1990 ozone season (May through September) average daytime only  $(10:00-18:00)$  ozone concentrations. Temperature is the 1990 ozone season daily maximum. Dilution Rate is the 1990 ozone season harmonic mean. <sup>*c*</sup> Populationweighted year-2000 annual average  $PM_{2.5}$  concentration. Dilution Rate is the 2000 annual harmonic mean. *<sup>d</sup>* Population-weighted sum of ozone concentration (1990 ozone season average daily 8-h maximum concentration) divided by ozone 8-h EPA standard (75 ppb), plus  $PM_{2.5}$ concentration (2000 annual average concentration) divided by  $\text{PM}_{2.5}$ annual EPA standard (15  $\mu$ g m<sup>-3</sup>). <sup>\*</sup>Statistical significance: *p* < 0.1. *\*\* p* < 0.05. *p* < 0.01.

mixed layer.<sup>33</sup> We temporally summarize dilution rates using harmonic mean $^{34}$  and then spatially summarize for each UA using arithmetic mean.

2.3.3. Transportation. Transportation networks may affect concentrations of traffic-related pollutants by influencing mode share, trip length, and number of trips. We include in the model transit supply (rail and nonrail transit route-kilometers per square kilometer) from Bento et al.<sup>3</sup> and annual household VKT from national surveys.<sup>35</sup>

2.3.4. Other Urban Characteristics. Additional explanatory variables included here are land area as a measure of city size, average income per person (U.S. Census Bureau) as a measure of wealth, and U.S. region (binary variable indicating a location east versus west of the Mississippi River) to control for west-east transport of ozone and PM. We tested income and income-squared in the regression models as previous studies have found nonlinear (parabolic) relationships between air pollution and wealth.<sup>36</sup>

2.4. Stepwise Linear Regression Models. We use forward stepwise linear regression, accepting new independent variables if they are statistically significant  $(p < 0.1)$  and avoiding multicollinearity (variance inflation factor [VIF] <5; Tables S4-S5 provide multicollinearity analyses).



Figure 1. Percent change in population-weighted air pollution levels (ozone,  $PM_{2.5}$ , long-term air quality index [LAQI]) associated with increasing the independent variable across the interquartile range, holding all other variables constant at the arithmetic mean value. Statistical significance: \**p* < 0.1; \*\**p* < 0.05; \*\*\**p* < 0.01.

#### 3. RESULTS AND DISCUSSION

Model results for all criteria pollutants are presented in the SI (Figures S4-S8, Tables S6-S16). For concision, we present here three models: ozone,  $PM_{2.5}$ , and the aggregate long-term air quality index (LAQI). Results (Table 3, Figure 1) indicate that urban form is associated with air quality, even after accounting for other common explanatory variables. The magnitude of impact is comparable to those for climatic factors, which are widely considered to be important for air pollution. Model adjusted-*R* 2 values (0.27 to 0.34) suggest limited model predictive power, but the model *p*-values ( $p < 0.0001$ ) indicate that the models have strong statistical significance in illustrating trends in the data.

Of the urban form variables tested, those describing spatial distributions of population (population centrality, population density) were the strongest predictors of air quality, and in opposing directions: population centrality is associated with lower population-weighted ozone,  $PM_{2.5}$  and aggregate pollutant levels  $(p < 0.01)$ , whereas population density is associated with higher population-weighted  $PM_{2.5}$   $(p < 0.01)$  and aggregate pollutant levels ( $p < 0.05$ ). (Population centrality is not highly correlated with population density;  $R^2 = 0.008$ ; Table S4. Figures 2 and S9 illustrate population centrality versus density.) Transit supply is associated with lower population-weighted  $PM_{2.5}$  concentrations ( $p < 0.1$ ). Results and discussion regarding the other criteria pollutants are in the SI. For example, road density is associated with higher population-weighted concentrations of  $PM_{10}$  ( $p < 0.05$ ) and TSP ( $p < 0.01$ ).

Climatic factors are statistically significant predictors of concentrations, and in the expected direction: dilution is negatively associated with concentrations ( $p < 0.01$ ; more dilution yields lower concentrations), and temperature is positively associated with ozone concentrations ( $p < 0.01$ ; high temperatures yield increased ozone formation). The eastern region variable is positively associated with ozone ( $p < 0.05$ ) and with  $PM_{2.5}$  ( $p < 0.01$ ), probably reflecting west-east pollution transport, plus other regional differences affecting pollution levels (e.g., biogenic emissions, environmental policy, types and locations of industrial emissions).

Our finding that concentrations decrease with population centrality is consistent with  $Stone<sup>24</sup>$  (who finds a negative, but not statistically significant at  $p < 0.10$ , relationship between ozone exceedences and the SGA composite centeredness index)



Figure 2. Four urban areas (each with population 1.5-2.2 million persons in year-1990) illustrating high- and low-population density and centrality. Maps show the 1990CensusTract population density (data and boundary filesfromtheU.S.Census Bureau). See also Figure S9,which presents a similar illustrationfor 4 smallerUAs.

and is likely attributable in part to differences in population distributions in relation to air pollution. Ozone concentrations typically peak at distance from urban centers; in a more decentralized urban area, population is likely to be relatively greater in these high-ozone areas. Population centrality may also relate to air pollution through travel demand management; Bento et al.<sup>3</sup> report that annual VKT decreases with population centrality. The finding that population-weighted air pollutant concentrations increase with population density is consistent with modeling studies.<sup>10,20</sup> The finding that  $PM_{2.5}$  concentrations decrease with transit supply perhaps reflects the net impact of vehicle travel-distance (and emissions) increasing for public transit but decreasing for private vehicles.

The predicted magnitude of air quality impacts associated with changes in urban form is comparable to impacts for climatic factors. Figure 1 shows percent changes in air pollution levels associated with interquartile range (IQR) changes in urban form and climatic factors, holding all other variables constant at their arithmetic average value. Models predict 4% to 12% changes in population-weighted air pollutant levels for IQR changes in urban form variables, compared to the 7% to 15% changes in population-weighted air pollutant levels for IQR changes in climatic factors. (Impacts of climate on air pollution may differ for long-term averages versus short-term peaks.) Table 4 shows predicted changes in population-weighted air pollutant levels associated with IQR increases in urban form variables and then lists sample cities (with similar population size and located in the same U.S. region) that reflect an IQR change in that variable. For example, increasing population centrality by the IQR (for example, from Toledo, OH levels to Albany, NY levels) is associated with a 2.9 ppb (on average, 6.4%) decrease in populationweighted ozone concentration and a  $1.3 \mu g m^{-3}$  (on average, 9.3%) decrease in population-weighted  $PM_{2.5}$  concentration. These estimates for changes in air pollution concentration associated with moderate changes in urban form are of the same magnitude as predictions from modeling studies [∼4% change in ozone and PM<sub>10</sub> concentrations;<sup>15</sup> ∼20% change in PM<sub>2.5</sub> concentrations;<sup>16</sup> ∼2%-10% change in ozone concentrations $^{21}$  and also are of the same magnitude as observed concentration changes in U.S. nonattainment areas between 2000 and 2008 [-7% change in ozone 8-h concentrations,  $-11\%$  change in PM  $_{2.5}$  annual average concentrations<sup>2</sup>].

To put the results in Table 4 into perspective, consider the estimated health benefit from the decrease in populationweighted  $PM<sub>2.5</sub>$  concentrations associated with an IQR change in population centrality. Assuming a 4% change in mortality rate per 10  $\mu$ g m<sup>-3</sup>  $\text{PM}_{2.5}^{37}$  and U.S.-average mortality rates [804 deaths annually per 100,000 persons<sup>38</sup>], a reduction of  $1.3 \mu$ g m<sup>-3</sup> PM<sub>2.5</sub> would reduce annual mortality rates by ∼40 deaths per year in a city with 1 million people. Employing EPA's central estimate for Value of a Statistical Life (\$9 million<sup>39</sup>) yields a financial value to those health improvements, ∼\$400 million per year. This backof-the-envelope calculation highlights the potential importance of changes in air pollution, even for the modest shifts (e.g., 1.3  $\mu$ g  $m^{-3}$  PM<sub>2.5</sub>) given in Table 4.

Air quality strategies that involve changes in one urban form attribute likely impact other attributes, potentially including attributes not evaluated in our study. For example, changes in population distributions may impact the demand for transit Table 4. Changes in Population-Weighted Air Pollution Concentrations Associated with Increasing the Independent Variable Across the Interquartile Range (IQR) (Which Reflects a Change in Urban Form from UA1 to UA2), Holding All Other Variables Constant at Arithmetic Mean



*a* For example, population centrality is 1.3 units greater for Albany as for Toledo, approximately an IQR difference. Modeling results indicate that this population centrality increase is associated with a  $1.3 \mu$ g m<sup>-3</sup> decrease in annual average population-weighted PM<sub>2.5</sub> concentration (9% of average population-weighted  $PM<sub>2.5</sub>$  concentrations).

supply and/or feasibility of transit supply. Alternately, changes in transit supply may change population distributions through shifts in relative accessibility and/or desirability of locations. Such patterns, though important, are difficult to discern via a crosssectional study such as the one presented here. Changes in urban form likely have cobenefits or trade-offs among environmental, health, and other goals. For example, steps to reduce urban air pollutants from motor vehicles may prove beneficial for physical activity levels<sup>40-42</sup> and transportation- $CO_2$  emissions.<sup>43,44</sup>

Our use of regulatory data to estimate long-term populationweighted ambient pollution concentrations at the urban scale is both a strength and a limitation of this study. It is a strength because the data represent widely accepted "gold standard" measurements of air pollution and because our results are based on empirical evidence rather than models or theory. However, monitors are spatially sparse, which may introduce error in estimating population-weighted concentrations.<sup>45</sup> Of the 111 UAs in our sample, only 3 UAs (Chicago, IL; Phoenix, AZ; Washington, DC) have more than 10 monitors for ozone, and 3 UAs (Chicago, IL; Dallas, TX; Philadelphia, PA) for PM<sub>2.5</sub>. Most UAs have fewer than 3 monitors per pollutant (Figure S3). If concentration estimates with better spatial precision were available across a wide section of UAs, we would be able to incorporate those estimates in our approach. As a second limitation, because monitoring stations are sparse, we are unable to explore here research questions related to the distribution of exposures among the population (e.g., high- versus low-income neighborhoods). As a third limitation of our method, we studied population-weighted ambient concentrations only and did not investigate exposures indoors or in vehicles. Finally, as with any cross-sectional analysis, our results demonstrate correlation, not causation. Future observational studies could usefully employ longitudinal designs to better explore causality between changes in the built environment and changes in air quality. The consistency between empirical results presented here and modeling studies (see above) gives weight to the hypothesis that trends observed here reflect a causal relationship.

A contribution of this work to previous empirical studies is that the individual urban form metrics at the UA scale more clearly elucidate relationships with urban air quality compared to metropolitan-scale composite indices (e.g., SGA sprawl indices). For example, although population density and population centrality are both associated with regional compactness (as

measured by SGA composite index, the urban form metric used by Schweitzer and Zhou<sup>25</sup>), we find that these two attributes relate to pollution concentrations in opposing directions. This finding highlights the importance of considering urban form metrics separately.

Our results indicate that the statistical power in predicting long-term urban air quality is similar for urban form as for local climate. Research on the latter issue dwarfs research on the former issue. For example, Web of Knowledge identified 671 articles on ambient air pollution and meteorology versus 24 articles on air pollution and urban form (see the SI). While our specific findings are useful, an important take-away message is the need for greater understanding on how urban form impacts air quality.

In our analysis, the urban form variables with the strongest statistical power for predicting air pollution concentrations are population centrality (correlated with lower concentrations) and population density (correlated with higher concentrations); their magnitude of impact is comparable to climatic factors and also to concentration changes observed in U.S. cities during the 2000s. Thus, at a systems-level scale (UAs), spatial distributions of population are a significant predictor of observed air quality. Effective physical planning approaches to improve air quality and exposures might consider spatial distributions of population and in particular potential air quality trade-offs between population centrality and population density.

### **ASSOCIATED CONTENT**

**6** Supporting Information. Model results and discussion for additional EPA criteria pollutants: carbon monoxide, lead, nitrogen dioxide,  $PM_{10}$ , sulfur dioxide, TSP. This material is available free of charge via the Internet at http://pubs.acs.org.

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# Supporting Information (SI)

**Title:** Air quality and urban form in US urban areas

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**Number of pages:** 32 **Number of tables:** 17

**Number of figures:** 9

# **1. Methods Supporting Information**

In addition to the core models for ozone and  $PM_{2.5}$  in the main paper, here we present details for the stepwise linear regression models for the remaining criteria pollutants (and alternate measures of ozone and of the long-term air quality index).

**1.1. Dependent Variables.** As described in **Table S1**, EPA monitor data are for year-1990 for the six criteria pollutants reported in that year. For the two criteria pollutants ( $PM_{10}$  and  $PM_{2.5}$ ) not reported in 1990, EPA data are for year-1995 ( $PM_{10}$ ) and year-2000 ( $PM_{2.5}$ ). For the six criteria pollutants monitored year-round, we calculate annual average concentrations. For the two criteria pollutants (ozone and carbon monoxide) monitored seasonally, we calculate the 5-month seasonal average concentrations (5-month summer average for ozone; 5-month winter average for carbon monoxide). Models for lead and for  $PM_{10}$  predict the natural log of population-weighted concentrations because lead and  $PM_{10}$  concentration data are log-normally distributed. The remaining models predict populationweighted concentrations. Additionally, we present stepwise linear regression models for 4 alternate population-weighted summer ozone concentration metrics ([1] 24-hour average; [2] 8-hour nighttime average (22:00-06:00); [3] 8-hour maximum average, which is the EPA's regulatory metric; [4] year-2000 8-hour daytime average) and 2 alternate population-weighted long-term air quality indices ([1] LAQI of two priority pollutants: ozone and  $PM_{2.5}$ ; and [2] LAQI of 8 pollutants: carbon monoxide, lead, nitrogen dioxide, ozone,  $PM_{10}$ ,  $PM_{2.5}$ , sulfur dioxide, total suspended particulates).

**Equation S1** presents the calculation of population-weighted air pollutant concentration (*C*) for each UA, where  $c_i$  is the interpolated concentration (using inverse distance-weighting of the long-term average concentrations from the 3 nearest monitors within 50 km) for each 1-km gridcell center,  $i$ , within the UA;  $p_i$  is the estimated population in each 1-km gridcell,  $i$ , within the UA; and  $n$  is the number of 1-km gridcell centers within the UA. **Figure S2** presents boxplots of the population-weighted pollutant concentrations.

(Equation S1)

\n
$$
C = \frac{\sum_{i=1}^{n} c_i p_i}{\sum_{i=1}^{n} p_i}
$$

**1.2. Independent Variables. Figure S3** presents boxplots of the independent variables, including measures of urban form, transportation infrastructure, climate, region, income and land area.

*1.2.1. Urban form datasets.* **Table S2** summarizes ten published datasets of empirical measures of urban form for US cities.

 *1.2.2. Temperature metrics.* We tested the following temperature metrics in preliminary regressions for time periods matching the air pollution data: Heating Degree Days (HDD; base 18.3°C [65 °F]), Cooling Degree Days (CDD; base 18.3°C [65 °F]), average daily temperature, average maximum daily temperature, average minimum daily temperature. In the final regression models, we employed the temperature metric with highest predictive power for each pollutant: 5-month summer average daily maximum temperature (ozone) and annual HDD (NO<sub>2</sub>; SO<sub>2</sub>). (CDD, HDD and average daily temperature have similar predictive power for  $NO_2$  and  $SO_2$ . Models for  $NO_2$  and  $SO_2$  employing CDD, HDD, or average daily temperature yield consistent results. None of the temperature metrics tested were statistically significant predictors of CO, lead,  $PM_{2.5}$ ,  $PM_{10}$ , or TSP.)

**1.3. Stepwise Linear Regression Models.** This analysis focused on daytime only concentrations of ozone to control for the effect of  $NO_x$  titration at night. **Table S3** illustrates the effect of including nighttime ozone concentrations by comparing models for alternate population-weighted ozone concentration metrics: daytime only, nighttime only, and 24-hour concentrations. The two ozone metrics that include night hours (24-hour average and nighttime only average) are negatively associated (*p*<0.05) with annual VKT (i.e., UAs with higher VKT have lower population-weighted ozone concentrations), whereas the metrics that do not include night hours show no association with VKT. This apparently reflects  $NO<sub>x</sub>$  titration of ozone at night.

For comparison, we generated a year-2000 5-month summer daytime only ozone model (**Table S3**). The year-2000 ozone model results are consistent with the year-1990 ozone model results (positive association with temperature  $[p<0.01]$ ; negative association with population centrality  $[p<0.01]$  and dilution rate  $[p<0.01]$ ), and with the year-2000 PM<sub>2.5</sub> results (positive association with population density  $[p<0.05]$ ; negative association with transit supply  $[p<0.05]$ ).

As part of a multicollinearity analysis, **Table S4** presents a correlation matrix of independent variables. The highest correlation between independent variables included in models is for transit supply and population density in the PM2.5 model. As shown in **Table S5**, multicollinearity is avoided (variance inflation factor  $\lt 5$ ) for the PM<sub>2.5</sub> model including both transit supply and population density, with consistent results (and variance inflation factor  $\langle 2 \rangle$  for alternate PM<sub>2.5</sub> models including either transit supply or population density (but not both metrics).

# **2. Results and Discussion Supporting Information**

As discussed for ozone and  $PM_{2.5}$  in the main paper, our results for the additional six criteria pollutants (**Figure 4; Tables S6-S16)** support the findings that: (1) urban form is associated with air quality, even after accounting for other common explanatory variables, and (2) the magnitude of impact is significant compared to climatic factors widely considered to be important for air pollution. Although the range of model adjusted  $R^2$  (0.06 to 0.51) suggests limited model predictive power across criteria pollutants, the model *p*-values ( $p$ <0.001 for all pollutants except lead (ln)  $[p<0.05]$  and the LAQI of the 8 pollutants  $[p<0.05]$ ) indicate that the models illustrate underlying trends in the datasets with statistical significance. **Figures S5-S8** present regression model residual plots, which illustrate that the model residuals are approximately normally distributed.

Considering all pollutants (**Figure S4; Table S6**) the most robust urban form findings are for population density, road density, and population centrality. For those three metrics, results are statistically significant for two or more pollutants, with all regression coefficients in the same direction. Greater density of people, and of roads, is associated with higher levels of population-weighted air pollutant concentrations, whereas greater population centrality is associated with lower levels. Population density is associated with increased levels of population-weighted carbon monoxide  $(p<0.1)$ , nitrogen dioxide ( $p<0.01$ ), PM<sub>2.5</sub> ( $p<0.01$ ) and PM<sub>10</sub> ( $p<0.05$ ), and road density is associated with increased levels of population-weighted  $PM_{10}$  ( $p<0.05$ ) and total suspended particulates ( $p<0.01$ ). Greater population centrality (i.e., greater share of population living close to the urban core) is associated with lower levels of population-weighted ozone  $(p<0.01)$ , PM<sub>2.5</sub>  $(p<0.01)$ , and PM<sub>10</sub> (*p*<0.01). Additionally, transit supply and city shape (i.e., circularity of urban form) are associated with lower levels of population-weighted air pollutants, but results are statistically significant for only one pollutant. Transit supply is associated with decreased levels of population-weighted  $PM_{2.5}$  ( $p<0.1$ ) and city shape is associated with decreased levels of population-weighted carbon monoxide  $(p<0.01)$ .

Climatic factors are statistically significant predictors of air pollution, and in the expected direction. Dilution rate is associated with decreased levels of population-weighted carbon monoxide  $(p<0.01)$ , lead ( $p$ <0.05), nitrogen dioxide ( $p$ <0.01), ozone ( $p$ <0.01), PM<sub>2.5</sub> ( $p$ <0.01), PM<sub>10</sub> ( $p$ <0.01), and sulfur dioxide (*p*<0.05). Average daily maximum temperature is associated with increased levels of population-weighted ozone (*p<*0.01) (i.e., higher temperatures yield higher daytime ozone concentrations), and annual heating degree days are associated with increased levels of populationweighted nitrogen dioxide  $(p<0.05)$  and sulfur dioxide  $(p<0.05)$  (i.e., increased need for heating of buildings [i.e., lower temperature] is associated with increased population-weighted air pollutant concentrations; perhaps a reflection of greater fuel-use for winter heating or more frequent inversions in colder climates).

The predicted magnitude of impact of urban form on air pollution is significant compared to the predicted magnitude of impact of climatic factors. **Figure S4** shows the percent change in populationweighted air pollutant levels associated with increasing the independent variables across the interquartile range (IQR), holding all other variables constant at arithmetic mean value. Increasing individual urban form factors by 1-IQR is associated with 4% to 27% changes in population-weighted

air pollutant levels, and increasing individual climate factors by 1-IQR is associated with 7% to 30% changes in population-weighted air pollutant levels.

Here, we provide details for the Web of Knowledge search results presented in the main text. Web of Knowledge identified 24 articles on ambient air pollution and air quality [topic search terms: ("air quality" OR "air pollution") AND ("ambient" OR "outdoor") AND ("urban form" OR "urban design" OR "urban planning" OR "city form" OR "city design" OR "city planning")] compared to 671 articles on ambient air pollution and meteorology [topic search terms: ("air quality" OR "air pollution") AND ("ambient" OR "outdoor") AND ("meteorology" OR "climate")] on June 11, 2011. The 24 articles identified with the urban form search terms are listed below.

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Table S1. Air pollution data inclusion criteria and descriptive statistics **Table S1.** Air pollution data inclusion criteria and descriptive statistics





"Monitor inclusion criteria: (1) observations reported for at least 75% of expected sampling days in study period, where the number of expected sampling days is based on typical sampling frequency over the study period, a *a*Monitor inclusion criteria: (1) observations reported for at least 75% of expected sampling days in study period, where the number of expected sampling days is based on typical sampling frequency over the study period, and (2) not source-oriented (i.e., "ambient") monitor. Of the 2,552 criteria pollutant monitors located in the 111 UAs evaluated, 734 monitors (29%) were eliminated under the inclusion criteria. Of the 734 monitors

S10

eliminated, 456 monitors were eliminated under the minimum observations reported criterion, 363 monitors were eliminated under the ambient eliminated, 456 monitors were eliminated under the minimum observations reported criterion, 363 monitors were eliminated under the ambient criterion, and 85 monitors were eliminated under both inclusion criteria. criterion, and 85 monitors were eliminated under both inclusion criteria.

*b*Arithmetic Mean (Arithmetic Standard Deviation)  $^b$  Arithmetic Mean (Arithmetic Standard Deviation)

*c*Geometric Mean (Geometric Standard Deviation) 'Geometric Mean (Geometric Standard Deviation) <sup>d</sup>LAQI is the population-weighted sum of the long-term concentrations for each of the 8 pollutants evaluated divided by their respective long*d*LAQI is the population-weighted sum of the long-term concentrations for each of the 8 pollutants evaluated divided by their respective longterm NAAQS, as shown in Table S17. term NAAQS, as shown in **Table S17.** 





 $a<sup>a</sup>MSA$  = Metropolitan Statistical Areas, as defined by US Census; UA = Urban Area, as defined by US Census,  $EUA =$  Extended Urban Area, as defined by Cutsinger et al.<sup>S3</sup>

Jaret et al.<sup>S11</sup> provides a recent review of empirical measures of urban sprawl.

Table S3. Analysis of alternate summer ozone metrics. Standardized coefficients<sup>a</sup> for stepwise linear regression models predicting population-weighted ozone concentrations (5-month summer 1990; 5 month summer 2000).



<sup>a</sup>Coefficient standardized to interquartile ranges (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted ozone concentration).

<sup>b</sup>The sample size (number of UAs with at least 1 monitor) differs across ozone metrics because there are 9 more EPA monitors with complete data (at least 75% of expected observations) for the 8-hour averages than for the 24-hour averages.



*c*Region (binary variable) and road density have moderate correlation (*r*=-0.57) but were not selected together in regression models. 'Region (binary variable) and road density have moderate correlation  $(r=0.57)$  but were not selected together in regression models. *b*The two temperature variables have moderate correlation (*r*=-0.85) but were not offered together in stepwise regression models.  $b$ The two temperature variables have moderate correlation ( $r=0.85$ ) but were not offered together in stepwise regression models.

**Table S5.** Multicollinearity analysis for  $PM_{2.5}^{\text{a}}$  models. Standardized coefficients<sup>b</sup> and variance inflation factors (VIF) with and without transit supply and population density (*r=*0.69) included as independent variables.

	Standardized coefficient <sup>b</sup> (VIF <sup>c</sup> )						
Independent Variable	Model 1: stepwise regression with 11 independent variables (core $PM_{2.5}$ model)	Model 2: stepwise regression without population density (10 independent variables)	Model 3: stepwise regression without transit supply (10) independent variables)				
Intercept	$2.7***$	$3.3***$	$2.9***$				
Urban Form							
<b>City Shape</b>							
Jobs-Housing Imbalance							
<b>Population Centrality</b>	$-0.31***(1.1)$	$-0.27***(1.1)$	$-0.31***(1.1)$				
<b>Population Density</b>	$0.36***(2.4)$		$0.21**$ (1.3)				
Road Density							
Climate							
<b>Dilution Rate</b>	$-0.28***(1.2)$	$-0.21***(1.0)$	$-0.26***(1.2)$				
Temperature							
Transportation							
<b>Transit Supply</b>	$-0.14*(2.0)$						
<b>VKT</b>							
<b>Other Urban Characteristics</b>							
Income							
Land Area							
Region	$0.67***(1.2)$	$0.55***(1.1)$	$0.65***(1.2)$				
Model adjusted $R^2$	0.29	0.22	0.25				
Model $p$ -value	$0.0000$ ***	$0.0000$ ***	$0.0000$ ***				

<sup>*a*</sup>Models predict population-weighted year-2000 annual average  $PM_{2.5}$  concentrations ( $\mu$ g m<sup>-3</sup>).

<sup>b</sup>Coefficient standardized to interquartile range (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted year-2000 annual average  $PM<sub>2.5</sub> concentration$ .

*<sup>c</sup>*Variance inflation factor

Table S6. Standardized coefficients<sup>a</sup> for stepwise linear regression models predicting population-weighted air pollutant levels **Table S6.** Standardized coefficients*a* for stepwise linear regression models predicting population-weighted air pollutant levels



*b***Models for lead and PM**<sub>10</sub> predict the natural log of population-weighted concentrations. <sup>b</sup>Models for lead and PM<sub>10</sub> predict the natural log of population-weighted concentrations.

*c*Long-term air quality index is a population-weighted aggregate measure of the 8 pollutants as described in **Table S17.**  'Long-term air quality index is a population-weighted aggregate measure of the 8 pollutants as described in Table S17.

*d*Temperature metric is 1990 5-month summer average daily maximum temperature (ozone) or 1990 Heating Degree Days (NO2; SO2).  ${}^{d}$ Temperature metric is 1990 5-month summer average daily maximum temperature (ozone) or 1990 Heating Degree Days (NO<sub>2</sub>; SO<sub>2</sub>).

<sup>e</sup>Income variable is the square of average income per person. *e*Income variable is the square of average income per person.

\*Statistical significance: \**p*<0.1; \*\**p*<0.05; \*\*\**p*<0.01 \*Statistical significance: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table S7.** Stepwise linear regression model results for carbon monoxide<sup>*a*</sup> ( $n = 90$ )

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (ppm) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IQR^{\uparrow \S}$	$p$ -value	VIF
(Intercept)	2.16	3.52			$0.0000$ ***	
City Shape (unitless)	$-0.609$	$-0.248$	$-0.15$	$-11\%$	$0.0065***$	1.13
Dilution Rate $(m^2 s^{-1})$	$-5.84e-4$	$-0.287$	$-0.18$	$-12\%$	$0.0001$ ***	1.25
Land Area $(km^2)$	$-1.11e-4$	$-0.144$	$-0.088$	$-6.4\%$	$0.0185**$	1.05
<b>Population Density</b>	2.84e-4	0.167	0.10	8.2%	$0.0568*$	1.32
(persons $km^{-2}$ )						
Region (binary)	$-0.283$	$-0.462$	$-0.28$	$-19%$	$0.0016***$	1.12
Model adjusted $R^2 = 0.36$		Model <i>p</i> -value = $0.0000$ ***				

<sup>a</sup> Population-weighted 1990 5-month winter (November through March) average carbon monoxide concentration (ppm). Dilution Rate is the 1990 5-month winter harmonic mean.

**Table S8.** Stepwise linear regression model results for lead  $\left[\ln\right]^b$  (*n* = 52)

Variable	Coefficient	Standardized $\Delta (\mu g \text{ m}^{-3})$ Coefficient <sup><i>t</i></sup>	per IOR $\uparrow^{\S}$	$\Delta$ (%) per $IOR^{\uparrow \S}$	$p$ -value	VIF
(Intercept)	$-2.95$	$-2.99$			$0.0000$ ***	
Dilution Rate $(m^2 s^{-1})$	$-5.43e-4$	$-0.187$	$-0.0067$	$-17\%$	$0.0485**$	
Model adjusted $R^2 = 0.06$		Model <i>p</i> -value = $0.0485**$				

<sup>b</sup>Natural log of population-weighted 1990 annual average lead concentration ( $\mu$ g m<sup>-3</sup>). Dilution rate is the year-1990 harmonic mean.

**Table S9.** Stepwise linear regression model results for nitrogen dioxide<sup>c</sup>  $(n = 55)$ 



*c* Population-weighted 1990 annual average nitrogen dioxide concentration (ppm). Dilution Rate is 1990 annual harmonic mean. Temperature is 1990 annual heating degree days (base 18.3°C [65 °F]).

<sup>1</sup>Coefficient standardized to the interquartile range (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted air pollutant levels).

*§* Predicted change (or predicted percent change) in population-weighted air pollutant levels associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value.

**Table S10.** Stepwise linear regression model results for daytime ozone  $d(n = 100)$ 

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (ppm) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IOR\uparrow^{\S}$	$p$ -value	VIF
(Intercept)	$6.79e-3$	0.683	$\overline{\phantom{0}}$		0.5061	
Dilution Rate $(m^2 s^{-1})$	$-8.12e-6$	$-0.316$	$-0.0031$	$-6.6\%$	$0.0000$ ***	1.06
<b>Population Centrality</b>	$-2.37e-3$	$-0.290$	$-0.0029$	$-6.2\%$	$0.0035***$	1.19
(unitless)						
Region (binary)	$3.41e-3$	0.343	0.0034	8.0%	$0.0482**$	1.18
Temperature $(^{\circ}C)$	8.98e-4	0.618	0.0061	15%	$0.0001$ ***	1.40
Model adjusted $R^2 = 0.35$		Model <i>p</i> -value = $0.0000$ ***				

*d* Population-weighted 1990 5-month summer (May through September) average daytime ozone concentration (10:00-18:00) (ppm). Temperature is the 1990 5-month summer average daily maximum. Dilution Rate is the 1990 5-month summer harmonic mean.

**Table S11.** Stepwise linear regression model results for fine particulate matter  $(PM_{2.5})^e$  ( $n = 107$ )

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (µg m <sup>-3</sup> ) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IOR\uparrow^{\S}$	$p$ -value	<b>VIF</b>
(Intercept)	11.6	2.68			$0.0000$ ***	
Dilution Rate $(m^2 s^1)$	$-3.73e-3$	$-0.274$	$-1.2$	$-7.9\%$	$0.0000$ ***	1.25
<b>Population Centrality</b>	$-1.10$	$-0.308$	$-1.3$	$-8.9\%$	$0.0001***$	1.10
(unitless)						
<b>Population Density</b>	$4.08e-3$	0.360	1.6	12%	$0.0030***$	2.37
(persons $km^{-2}$ )						
Region (binary)	2.88	0.669	2.9	24%	$0.0000$ ***	1.17
Transit Supply (route-km)	$-4.36e-5$	$-0.138$	$-0.60$	$-4.1\%$	$0.0580*$	1.96
$km^{-2}$ )						
$\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\frac{1}{2}$ $\sim$ $\sim$ $\sim$	<b>B</b> $\bf{r}$ 1 1 - 11	$\bigcap$ $\bigcap$ $\bigcap$ $\bigcap$ $\bigcap$ $\bigcap$ $\bigcup$				

Model adjusted  $R^2 = 0.27$  Model *p*-value =  $0.0000$ \*\*\*

<sup>e</sup> Population-weighted 2000 annual average PM<sub>2.5</sub> concentration ( $\mu$ g m<sup>-3</sup>). Dilution Rate is 2000 annual harmonic mean.

<sup>1</sup>Coefficient standardized to the interquartile range (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted air pollutant levels).

*§* Predicted change (or predicted percent change) in population-weighted air pollutant levels associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value.

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (µg m <sup>-3</sup> ) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IQR^{\uparrow \S}$	$p$ -value	<b>VIF</b>
(Intercept)	3.25	10.9	-		$0.0000$ ***	
Dilution Rate $(m^2 s^1)$ [Income] <sup>2</sup> (\\$) Land Area $(km^2)$ <b>Population Centrality</b> (unitless)	$-2.49e-4$ $-1.309e-9$ $9.25e-5$ $-0.0549$	$-0.221$ $-0.321$ 0.201 $-0.233$	$-1.7$ $-2.4$ 1.5 $-1.7$	$-6.4\%$ $-9.1\%$ $6.2\%$ $-6.7\%$	$0.0003***$ $0.0001$ *** $0.0006***$ $0.0089***$	1.31 1.27 1.21 1.16
<b>Population Density</b> (persons $km^{-2}$ )	$1.97e-4$	0.244	1.8	7.5%	$0.0174**$	1.68
Road Density $(\%)$	0.0339	0.173	1.3	5.3%	$0.0191**$	1.23
Model adjusted $R^2 = 0.36$		Model <i>p</i> -value = $0.0000$ ***				

**Table S12.** Stepwise linear regression model results for coarse particulate matter (PM<sub>10</sub>) [ln]<sup> $f$ </sup> ( $n = 104$ )

*f*Natural log of population-weighted 1995 annual average  $PM_{10}$  concentration ( $\mu$ g m<sup>-3</sup>). Dilution Rate is the 1995 harmonic mean. Income is mean annual household income squared.





Model adjusted  $R^2 = 0.26$  Model *p*-value = 0.0001<sup>\*\*\*</sup><br><sup>8</sup>Population-weighted 1990 annual average sulfur dioxide concentration (ppm). Dilution Rate is the 1990 annual harmonic mean. Temperature is the 1990 annual heating degree days (base 18.3°C [65 °F]).

<sup>*I*</sup>Coefficient standardized to the interquartile range (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted air pollutant levels).

*§* Predicted change (or predicted percent change) in population-weighted air pollutant levels associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value.

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (µg m <sup>-3</sup> ) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IOR^{\uparrow \S}$	$p$ -value	VIF
(Intercept)	11.4	0.849	$\overline{\phantom{a}}$		$0.0647*$	
Road Density $(\%)$	10.6	0.946	12.7	27%	$0.0000$ ***	
Model adjusted $R^2 = 0.51$		Model <i>p</i> -value = $0.0000$ ***				

**Table S14.** Stepwise linear regression model results for total suspended particulates (TSP)<sup>*h*</sup> ( $n = 57$ )

*h*Population-weighted 1990 annual average TSP concentration ( $\mu$ g m<sup>-3</sup>).

**Table S15.** Stepwise linear regression model results for long-term air quality index of 8 pollutants<sup>*i*</sup> (*n* = 12)



 $\overline{P}$ Population-weighted index (unitless) of 8 pollutants (CO, lead, NO<sub>2</sub>, ozone, PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, TSP)

as described in **Table S17**.

**Table S16.** Stepwise linear regression model results for long-term air quality index of 2 pollutants<sup>*j*</sup> ( $n =$ 97)

Variable	Coefficient	Standardized Coefficient <sup><i>t</i></sup>	$\Delta$ (unitless) per IQR $\uparrow^{\S}$	$\Delta$ (%) per $IOR\uparrow^{\S}$	$p$ -value	<b>VIF</b>
(Intercept)	0.797	2.11	$\overline{\phantom{a}}$		$0.0548*$	
Dilution Rate $(m^2 s^{-1})$	$-4.00e-4$	$-0.332$	$-0.13$	$-7.5\%$	$0.0000$ ***	1.41
<b>Population Centrality</b>	$-0.0906$	$-0.295$	$-0.11$	$-6.8\%$	$0.0015***$	1.23
(unitless)						
<b>Population Density</b>	$2.13e-4$	0.201	0.076	4.9%	$0.0327**$	1.50
(persons $km^{-2}$ )						
Region (binary)	0.247	0.654	0.25	18%	$0.0004***$	1.45
Temperature $(^{\circ}C)$	$1.46e-2$	0.262	0.10	$6.5\%$	$0.0687*$	1.58
Model adjusted $R^2 = 0.29$		Model <i>p</i> -value = $0.0000$ ***				

*j* Population-weighted index (unitless) of 2 pollutants (ozone and PM2.5) as described in **Table S17**. Dilution Rate is 2000 annual harmonic mean. Temperature is 1990 5-month summer average daily maximum.

<sup>1</sup>Coefficient standardized to interquartile ranges (IQR) of dependent and independent variables. For example, a standardized coefficient of 0.2 would mean that a 1-IQR increase in the independent variable is associated with a 0.2-IQR increase in the dependent variable (population-weighted air pollutant levels).

*§* Predicted change (or predicted percent change) in population-weighted air pollutant levels associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value.





<sup>a</sup>Long-term air quality index (LAQI) is the population-weighted sum of long-term concentrations divided by long-term NAAQS (as in **Table S17** above**)**. We calculate 2 alternate long-term air quality indices: (1) index of 2 pollutants: ozone and  $PM_{2.5}$ , (2) index of 8 pollutants: CO, lead, NO<sub>2</sub>, ozone,  $PM_{2.5}$ ,  $PM_{10}$ ,  $SO_2$ , and TSP.

*b*National Ambient Air Quality Standards (United States Environmental Protection Agency)



**Figure S1**. Dependent variable boxplots (minimum, 25<sup>th</sup> percentile, median, 75<sup>th</sup> percentile, maximum).



Figure S2. Independent variable boxplots (minimum, 25<sup>th</sup> percentile, median, 75<sup>th</sup> percentile, maximum).



**Figure S3.** Number of included monitors and population-weighted concentrations (tertiles) for ozone (*n*  $= 100$ ) and PM<sub>2.5</sub> ( $n = 107$ ) for each of the 111 UAs evaluated.



**Figure S4**. Percent change in population-weighted air pollution concentrations associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value. Here, the long-term air quality index is a population-weighted aggregate measure of the 8 pollutants (see **Table S17)**. Temperature is 5-month summer average maximum daily temperature (ozone) or annual heating degree days (nitrogen dioxide; sulfur dioxide). For region (binary variable), reported percent change in air pollution concentration is for a heating degree days (nitrogen dioxide; sulfur dioxide). For region (binary variable), reported percent change in air pollution concentration is for a Figure S4. Percent change in population-weighted air pollution concentrations associated with increasing the independent variable across the interquartile range, holding all other variables constant at arithmetic mean value. Here, the long-term air quality index is a population-weighted aggregate measure of the 8 pollutants (see Table S17). Temperature is 5-month summer average maximum daily temperature (ozone) or annual change from western to eastern region. change from western to eastern region.



















Figure S9. Four urban areas (each with population 180,000 to 270,000 persons in year-1990) illustrating high- and low- population density and centrality. Maps show the 1990 Census Tract population density. Higher values of centrality (Bento et al.<sup>S1</sup>) indicate that a greater fraction of population lives near the Central Business District.

# **3. References for Supporting Information**

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