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Air Quality and Asthma Hospitalization: Evidence of PM_{2.5} Concentrations in Pennsylvania Counties

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Abstract

According to the World Health Organization, 235 million people around the world currently suffer from asthma, which includes approximately 25 million in the United States. There is substantial epidemiological evidence indicating linkages between outdoor air pollution and asthma symptoms, more specifically between concentrations of particulate matter and asthma. Using county level data for 2001-2014, a spatial panel framework is imposed based upon prevailing wind patterns to investigate the direct and indirect impacts of PM_{2.5} concentration levels on asthma hospitalization in Pennsylvania. This model controls for population density, precipitation, smoking rate, and population demographic variables. Results show that PM_{2.5} concentrations as measured at the county level have positive direct and indirect effects on asthma hospitalization. A one-unit increase in PM_{2.5} in one Pennsylvania county will add, on average \$1.29M (\$754,656 direct and \$539,040 indirect) to total annual asthma hospitalization costs with the state of Pennsylvania. This study highlights the need for realistic and accurate impact analyses of ambient air pollution on asthma that reflects the impacts on neighboring regions as well. In order to capture the spillover effects of health-related impacts from PM_{2.5} pollution, a wind direction algorithm to identify appropriate neighbors is important.

Keywords: PM_{2.5} concentrations, Asthma, Spatial econometrics, Wind pattern weight matrix, Spillover effects

JEL Classification: Q53, I18, Q40

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1 Introduction

Ambient air pollution adversely impacts air quality and human health (Nel (2005); Kampa and Castanas (2008); Anderson et al. (2012)). The National Ambient Air Quality Standards (NAAQS) set by the Environmental Protection Agency (EPA) include six principal pollutants (i.e., Carbon Monoxide (CO), Lead (Pb), Nitrogen Dioxide (NO₂), Ozone (O₃), Particulate Matters (PM), and Sulfur Dioxide (SO₂)) as criteria air pollutants (Environmental Protection Agency (2016)). Over the last few decades, air pollution concerns have changed from concentrations of SO₂ and coarse particles towards more traffic-related air pollutants (TAP) (i.e., nitrogen oxides (NO_x), small particles and organic compounds) (Pénard-Morand et al. (2010)). The national average trend of SO₂ air quality shows an 87% decrease between 1980-2016 (Environmental Protection Agency (2018a)). With decreasing trends in SO₂, ozone, and nitrogen dioxide, particulates have gained more attention (Brunekreef and Holgate (2002)).

The World Health Organization (WHO) named particulate matter (PM) as the pollutant that affects people more than any other pollutant (World Health Organization (2016)). The severity and magnitude of PM health impacts is a function of its size. The smaller the size of PM, the more potential there is to cause severe damage to the human body (Environmental Protection Agency (2018b)). The negative health impacts of PM are widely discussed in the literature (Pope III et al. (2009); Raaschou-Nielsen et al. (2013); Wang et al. (2014); Zhu et al. (2017)). More specifically, many researchers have investigated the effects of short-term and long-term exposure to PM and resulting asthma symptoms (Silverman and Ito (2010); Samoli et al. (2011); Iskandar et al. (2012); Zhang et al. (2015)).

The EPA has continuously updated its standards for criteria air pollutants since the passage of the Clean Air Act of 1990. For instance, the standards for PM have changed three times and ozone pollution standards have changed two times. One element of enforcement for these standards is designation of attainment or nonattainment by an area. Attainment/ nonattainment classification by EPA is based on the level of air pollutants. In the case of a geographic area where pollutant levels are below the NAAQS threshold, this area is categorized as an attainment area. Unlike an attainment area, a nonattainment area deals with persistent air quality problems and violates federal health-related standards for outdoor quality (Pennsylvania Department of Environmental Protection (2016)).

As a demonstration, Appendix I shows nonattainment designation for PM_{2.5} concentrations in Pennsylvania are located primarily at or adjacent to metropolitan areas in the southeast and southwestern portions of the state during the time-period 2001 to 2014. Pollution dischargers within nonattainment areas are required to comply with tighter environmental regulations than similar dischargers in attainment areas. For instance, in nonattainment areas, existing pollution sources are required to install "reasonably available control technology" (RACT) while new sources of pollution are required to achieve the "lowest available emission rate" in addition to the RACT requirement (Curtis (2018)).

The main objective in this research is to examine what factors, including PM_{2.5} concentrations, explain asthma hospitalization in Pennsylvania. Applying a spatial regression model, this analysis provides us with estimates of both within county and spillover effects among contiguous counties from PM_{2.5} concentrations. The spillover analysis allows us to document the existence of biases that would be found when using standard, non-spatial models in estimating the impacts of PM_{2.5} concentrations.

By imposing a prevailing wind pattern in deriving the weight matrix, positive and significant effects of PM_{2.5} concentrations are found to occur on asthma hospitalization both within county and in neighboring counties. These results reveal that county PM_{2.5} concentrations are associated

with higher asthma hospitalization in neighboring counties, and within the county itself. Thus, important spillover effects exist from the PM_{2.5} concentrations on asthma hospitalization.

The main contribution of this research to the literature is investigating the spillover effects of the sources of PM_{2.5} pollutions on asthma hospitalization. In addition, the study introduces a new approach to evaluating neighboring regions when analyzing the health effects of air quality. After examining the literature, no previous study has controlled for the spatial interaction between PM_{2.5} concentrations and asthma hospitalization, so that the regional aspects of PM_{2.5} concentrations have not been investigated. PM_{2.5} and other air pollutant concentrations move through the atmosphere and neglecting their transportation underestimates the real impact of air quality.

The rest of the manuscript proceeds as follows. Section 2 provides background information on national and states' trends in asthma and its associated costs to society. Section 3 discusses ambient air pollution and, specifically, PM_{2.5} concentrations and asthma. Section 4 explains the study area. Section 5 provides details of the model developed for this research. Section 6 describes the data and spatial data considerations. Section 7 provides the results and section 8 concludes with a discussion and policy implications.

2 Asthma: symptoms, time trend, and cost

Asthma is a chronic respiratory and inflammatory lung disease characterized by episodes or attacks of impaired breathing. Even though scientists argue that there is not a specific, well-known cause for asthma, a combination of environmental factors and genetics are considered as the disease triggers (Center For Disease and Control (2013a)). Being exposed to multiple environmental factors exacerbate asthma symptoms.(Akinbami et al. (2011); Akinbami et al. (2012)). list airway irritants such as tobacco smoke and air pollution, allergens, respiratory infections, stress and exercise among common asthma attack triggers that exacerbate symptoms. According to(Bostantzoglou et al. (2015)), asthma symptoms may include coughing, shortness of breath, wheezing, chest tightness and chest pain and be caused by inflammation and narrowing of small airways. Whether the disease severity is mild or persistent, a person's quality of life may be affected by asthma. People with a mild disease may suffer severe attacks as well as those with a more severe and persistent symptom.

2.1 National and state asthma trend

Since the early 1980s, asthma has shown an upward trend in all ages, genders, and racial groups in the U.S. ((Asher et al. (2006)); National Center for Health Statistics, 2017). About 25 million Americans currently suffer from asthma, about one in every 13 people. Asthma is leading chronic disease and the third leading cause of hospitalization among individuals under 18 years of age (Center For Disease and Control (2013b)). Figure 1 shows the number of current prevalence (current prevalence is defined as those who answered "yes" to both "Have you ever been told by a doctor or other health professional that you had asthma?" and "Do you still have asthma?") of asthma in the U.S. between 2001 and 2015. Even though the overall trend of asthma's current prevalence is increasing on both the national and the state levels over a period of 15 years, individual states follow a different pattern. The Behavioral Risk Factor Surveillance System (BRFSS) provides the current asthma prevalence on the state level. Figure 2 shows the current asthma prevalence among adults between 2001 and 2015 since data for current asthma prevalence among children is not available for all the states. Wyoming, Vermont, and Kansas are among the states experiencing a moderate increase in the number of adult current asthma prevalence between 2001 and 2015. Florida, Alabama, Pennsylvania, and Utah are among the high increase states for adult asthma

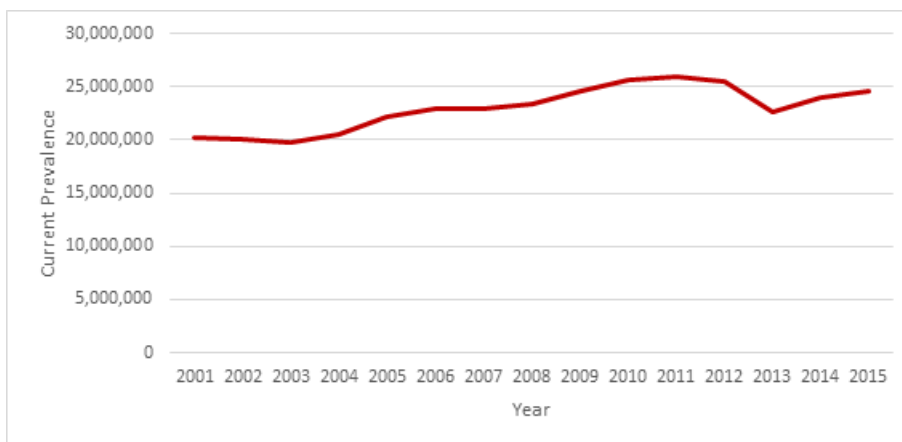


Figure 1: National current asthma prevalence, 2001-2015

prevalence. Compared to the average percentage increase in the U.S. over this time period (43%), Pennsylvania experienced a slightly higher increase rate at 47%.

2.2 The burdensome cost of asthma on society

Asthma can affect people of different age and racial groups, but is more common among minorities. Asthma represents a significant burden on individuals and society in terms of reducing productivity and increasing healthcare system demands (Crighton et al. (2012)). In estimating the total cost of disease, three classifications of cost are considered. Costs related to management, complementary investigation or treatment and other costs like domestic or professional preventive measures, assistance in home care, and transportation to medical visits are categorized as direct costs. Indirect costs include work-related losses whether it is related to temporary, early, or permanent disability and early mortality. Finally, costs related to reductions in quality of life, increases in pain or suffering, limitation of physical activities and job changes are classified as intangible costs (Nunes et al. (2017)).

According to the EPA’s asthma fact report, "asthma accounts for 14.2 million physician office visits, 439,000 discharges from hospital inpatient care, and 1.8 million emergency department visits each year" (EPA, 2016, p. 1). In 2008, 14.2 million reported asthma as the reason for missed days of work (Center For Disease and Control (2013a)). Reports show asthma accounts for 13.8 million missed school days in 2013 (United State Environmental Protection Agency (2011)).

In a number of studies, researchers estimate the costs associated with asthma. Stanford et al. (1999) assess the treatment cost of asthma in which the patient goes to the emergency department (ED). They report that, on average, each American paid \$234.48 for an ED visit in 1996-1997. In a more recent assessment, Wang et al. (2014) report an estimate of \$1,502 for asthma care charges in the ED based on data for 2006-2008. Average asthma hospitalization cost is much higher than an ED visit. Most of the cost of hospitalization belongs to inpatient nursing care and an average hospital visit of 3.8 days costs \$3,102.53. Barret et al. (2014) differentiate between asthma hospitalization costs for adults versus children. While each hospital stays for a child in 2010 averaged a total of \$3,600, the total cost for an adult was \$6,600 for each hospital stay.

What the previous studies have in common is a steady increase in asthma cost. The most recent estimates for the annual economic cost of asthma in the U.S. shows an increase from \$12 billion in 1994 to \$56 billion in 2011 (Niska et al. (2010); National Hospital Ambulatory Medical Care

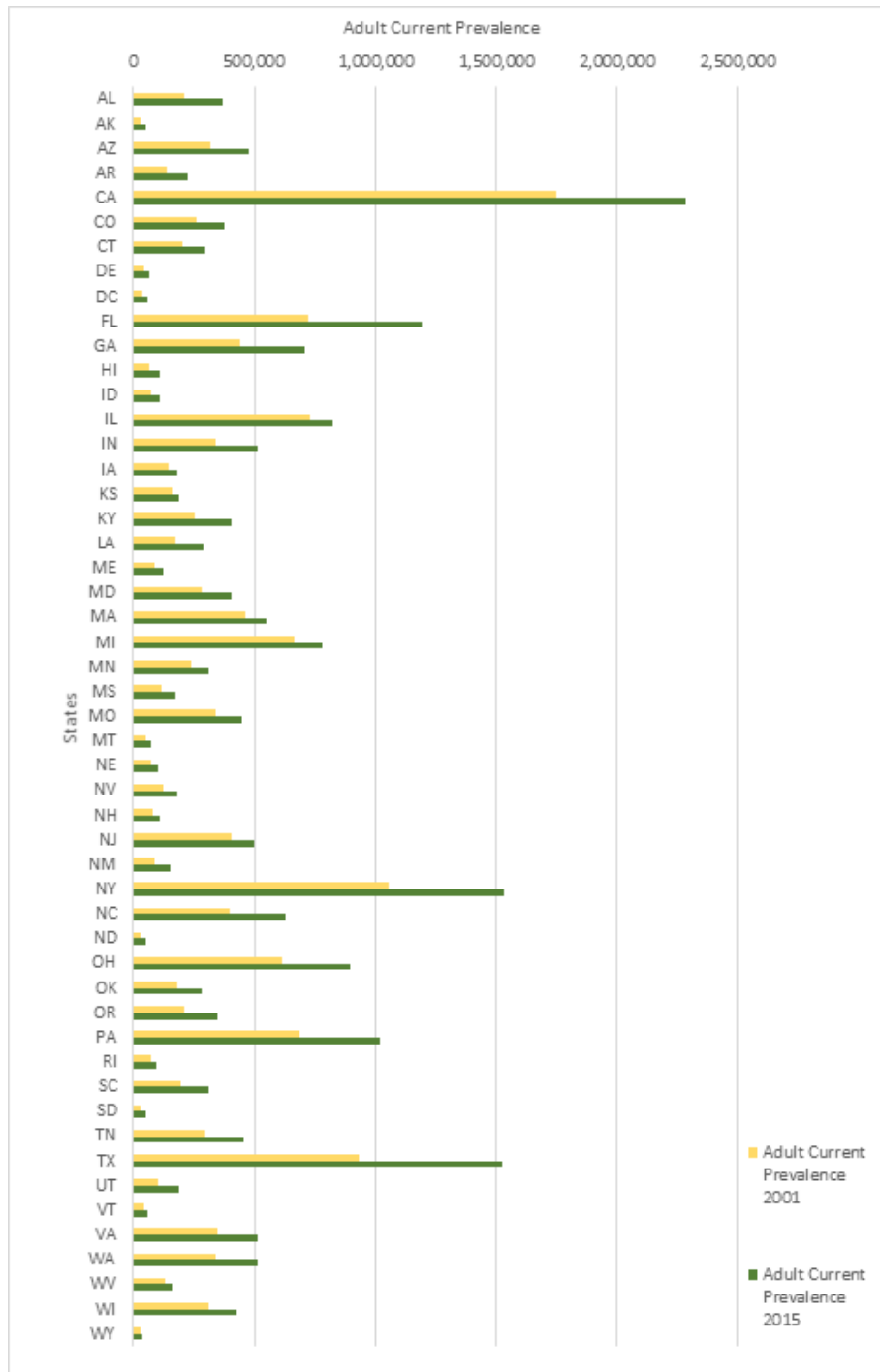


Figure 2: States' current asthma prevalence, 2001 and 2015

Survey (2011a); National Hospital Ambulatory Medical Care Survey (2011b)). Direct costs account for \$50.1 billion, mostly for hospital stays. The rest of the costs include lost pay from sickness or death and lost work output from missed school or work days (\$3.8 billion) and premature death (\$2.1 billion) (Barnett and Nurmagambetov (2011); Center For Disease and Control (2011)). The cost involving asthma hospitalization in Pennsylvania follows the same increasing trend over years (Pennsylvania Department of Health, 2012). Although there is no cure for asthma, it could be controlled by limiting exposure to triggers. In the next section, the connection between ambient air pollution and PM_{2.5} will be discussed.

3 Asthma and Ambient Air Pollution

Ambient air pollution impacts public health both on short and long-term bases. The most recent estimate reports that outdoor air pollution is responsible for more than 3% of the annual disability-adjusted life years lost in 2010 (Guarnieri and Balme (2014)). Traffic and fossil-fuel power generation contribute the largest shares to urban air pollution (Perera (2017); Cohen and Pope 3rd (1995)). With the increasing rate of urbanization in the U.S., more individuals face the negative effects of exposure to pollution. In general, the association between exposure to ambient air pollution and human health outcomes has been addressed in both older and more recent studies. Specifically, the following health conditions have received attention: cardiovascular and respiratory diseases (Schwartz and Morris (1995); Brook et al. (2004); Brook (2008)), lung cancer (Hamra et al. (2015); Cohen and Pope 3rd (1995); Raaschou-Nielsen et al. (2013); Nafstad et al. (2003)), low birth weight (Dugandzic et al. (2006); Pedersen et al. (2013); Yang and Chou (2015); Yang et al. (2017)), and morbidity and mortality (Currie and Neidell (2005); Krewski et al. (2009); Woodruff et al. (2007)).

The negative effects of PM_{2.5} on human health in general and particularly on asthma are at the core of this study. Many researchers address the effects of short-term and long-term exposure to PM_{2.5} (Tatum and Shapiro (2005); Eder et al. (2006); Künzli et al. (2009); Anderson et al. (2012); Harris et al. (2018); Veremchuk et al. (2018)). For example, a one-year exposure to $10\mu/m^3$ in PM_{2.5} has been estimated to increase mortality by 7.5% (Global Catholic Climate Movement, 2017). In another recent study, scientists show that an annual exposure increase of $10\mu/m^3$ for PM_{2.5} leads to an average loss of life expectancy between 9 and 11 years (Andersen (2017)). One of the issues with PM_{2.5} concentrations is that there is not an exact threshold for the concentration level. Recent studies show that the harmful effects are observed even in areas with concentration less than a third of the EPA current standard (Datz (2015)).

Inhalation of particulate matter has been estimated to be responsible for 500,000 excess deaths each year worldwide (United Nation & World Health Organization (1994)). In a study done by the Schneider et al. (2010), estimates for the health impacts of PM_{2.5} emitted from coal-fired power plants and automobiles in the U.S. show over 13,000 deaths, 9,700 hospitalizations, and 20,000 heart attacks in 2010 with a total monetized value of more than \$100 billion. Beelen et al. (2014), Schwartz et al. (2007), and Schneider et al. (2010) argue that long-term exposure to PM_{2.5} is associated with higher mortality risk, even when concentrations are below the standard limit. In other words, they believe there is no "safe threshold" for PM.

Glad et al. (2012), and United State Environmental Protection Agency (2011) show the impacts of PM_{2.5} on asthma emergency department visits and early deaths, respectively. Mann et al. (2010), Meng et al. (2010), Liu et al. (2008), Jacquemin et al. (2012), Malig et al. (2013), Samoli et al. (2011), and Silverman and Ito (2010) describe the effects of PM_{2.5} on asthma symptoms. Riedl and Diaz-Sanchez (2005), Namdeo et al. (2011), Ristovski et al. (2012), and World Health Organization

(2016) discuss the effects of PM_{2.5} on respiratory and cardiovascular disease. Lipsett et al. (1997) show the relationship between emergency room visits and exposure to PM₁₀. Nel (2005) relates the exacerbation of asthma and chronic bronchitis to exposure to PM₁₀ and PM_{2.5}. World Health Organization (2016) also reveals an association between PM_{2.5} plus PM₁₀ and lung cancer.

While numerous studies have analyzed the relationship between ambient air pollutants and asthma, evidence of this association on a regional scale is still mixed. The discussion presented by North Carolina Attorney General in 2006 arguing pollution from TVA's coal-fired power plants in Tennessee causing damages the health of North Carolina's residents is an example of the regional effects of ambient air pollution (Environmental Appeals Court (2008)). No previous research, however, has estimated the spatial spillover of PM_{2.5} pollution. Due to a misspecification issue when not accounting for spatial spillover, the results of any regression estimation may be biased. In other words, when using a non-spatial regression analysis, we assume health outcomes at a county basis, like asthma hospitalization, are independent of the pollution levels (PM_{2.5} concentrations for example) in neighboring counties. This assumption ignores the effects of PM_{2.5} concentrations on adjacent counties. By ignoring spatial spillover effects, the total effect of PM_{2.5} concentrations on health outcomes may be underestimated.

4 Study Area

Asthma related indicators are not available for all the states on a county level. Because of this data limitation, instead of a regional or national analysis, we focus on one state, Pennsylvania. Asthma in Pennsylvania is a serious concern. In 2017, the current asthma prevalence rate in Pennsylvania for adults was reported at 10.9%; that is far higher than the average rate among adults in the U.S. (7.6%) (Henry J Kaiser Family Foundation (2017)). Philadelphia, Allegheny, Delaware, Montgomery, and Berks are the counties with the highest number of asthma hospitalizations, while Sullivan, Forest, Juniata, Cameron, and Fulton counties have the lowest number of asthma hospitalizations.

According to 2015 Pennsylvania asthma fact sheet in 2013, the average cost for inpatient hospitalization was \$26,952 which is significantly higher than the national average (\$6,600) (Pennsylvania Department of Health (2015)). While the cost involving asthma hospitalization in Pennsylvania is much higher than the U.S. average, there are other states, such as California and Wisconsin where the average cost per asthma hospitalization is also much higher than the U.S. average. For example, the average cost per asthma hospitalization in California in 2010 was \$33,749. The total health care cost involving asthma and absenteeism for 2010 was estimated to be approximately \$1.7 billion in Pennsylvania. With an almost 50 percent increase projected by 2020, asthma costs are estimated to be approximately \$2.6 billion, which is an increased burden on the state economy at 0.34% of the state GDP as of 2017.

5 Models

A spatial regression model is used to investigate the impacts of PM_{2.5} concentrations on asthma hospitalization. Spatial regression models differ from regression models by inclusion of a spatial interrelationship between observations of geographic areas such as cities, counties, states, or even countries (Elhorst (2014)). In a spatial model, each observation belongs to a location whereas observations in a non-spatial regression are independent (LeSage and Pace (2009)). This locational linkage is a fundamental point for the observation dependency assumption in spatial regression.

Among the three types of spatial interaction effects, this study focuses on exogenous interactions among the independent variable (X). The spatial lag of X model (SLX) assumes that the depen-

dent variable for each observational unit depends on an independent variable from other units of observations.

$$\text{Independent variable of unit } j \longleftrightarrow \text{Dependent variable of unit } i \quad (1)$$

A SLX model can be expressed as

$$Y = \alpha \iota_N + X\beta + WX\theta + u \quad (2)$$

where Y is asthma hospitalization, WX denotes the interaction among the independent variables. β and θ represent a $K \times 1$ vector of parameters to be estimated. W is the spatial weight matrix which accounts for identification of neighbors. There are four types of spatial weight matrices commonly used in applied studies: (i) p -order binary contiguity matrices. Contiguity weight matrices assume only those units of observations that share a common border are neighbors ($p = 1$ also called first-order neighbors). When $p = 2$, neighbors and neighbors of neighbors are considered and so on; (ii) inverse distance matrices are based on distance between observation i and j ; (iii) q -nearest neighbor matrices when q is a positive and an integer number defined based on the research question by the researcher; and (iv) block diagonal matrices when a group of units have intercorrelation with each other, but not with the rest of the observations (Elhorst (2014)).

As pointed out by Anselin and Rey (1991), the proper choice of a spatial weight matrix is an important issue in empirical research. Generally, all mentioned forms of neighbors in spatial models deal with symmetric weight matrices. However, sometimes the most accurate definition of neighbors does not follow a symmetric form. Commuting flows in the transportation literature and regional labor market performance are two well-known examples of asymmetric spatial weight matrices. More related to our study, Chen et al. (2018)) capture the effect of wind direction on the PM10 concentrations at the municipal level in China as an example of a dynamic and asymmetric spatial weight matrix dependent on weather patterns.

Yang et al. (2017) and Yang and Chou (2015) explore the effects maternal exposure to downwind sulfur dioxide levels on the occurrence of low birth weight (LBW). They used zip code level of observations and control for wind direction by implementing a four-step procedure. Since these two studies did not apply a spatial regression model, this research is motivated by Cheng et al. (2014) and Chen et al. (2018) who introduce dynamic, asymmetric weight matrices into traffic modeling and PM10 concentrations, respectively. These authors argue that for some cases, such as network data and PM10 concentrations, a general homogeneous spatial weight matrix is inadequate and we need to apply a heterogeneous (and/or dynamic) spatial weight matrix.

Applying this same rationale, our study introduces an empirical model based on a weight matrix built upon prevailing wind direction. Based on this prevailing wind pattern, unit i is considered a neighbor for unit j if and only if it is located upwind of j . Since unit j is downwind of unit i , unit j is not considered a neighbor for unit i . Following this logic, a weight matrix is constructed based upon the annual average prevailing wind map for Pennsylvania counties (World Forecast Directory (2019)).

Figure 3 shows the annual prevailing wind directions in the U.S. Based upon this map, the prevailing wind direction in Pennsylvania is southwest to northeast. According to this prevailing wind direction, for instance, Washington County is considered to be a neighbor of Allegheny and Westmoreland Counties, but Allegheny County or Westmoreland County are not neighbors for Washington County. Since a weight matrix needs to be exogenous to the estimation procedure, a geographical weight matrix based upon prevailing wind direction fits this requirement. The notion of geographical proximity has been applied widely in previous literature (e.g., Jaffe (1989); Jaffe et al. (1993); Attila (2000); Chagas et al. (2016)).

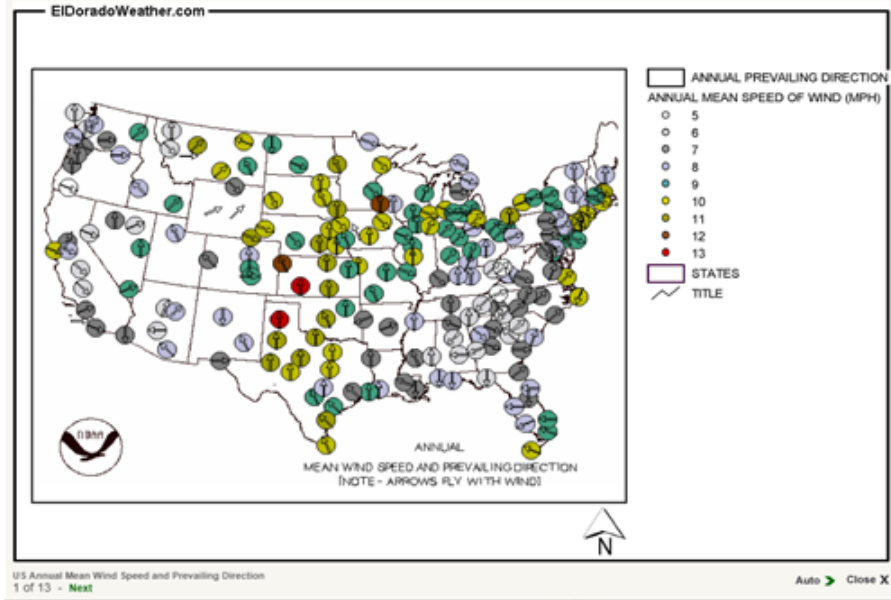


Figure 3: Annual prevailing wind direction

In addition to ambient PM_{2.5} concentrations, empirical studies have shown several other factors are associated with asthma incidents. Included among the independent variables are: smoking rate (Chen et al. (1999); Thomson et al. (2004); Gilliland et al. (2006)), population density (Leinberger (2010); Solé et al. (2007)), and Hispanic population (Center For Disease and Control (2013a)). Each control variable is expected to be positively correlated with asthma incidence. Per capita income level has been shown to be negatively correlated with asthma incidence (Kozyrskyj et al. (2010)), while weather variables of precipitation and humidity have had mixed effects in the literature (Jerrett et al. (2008); Ho et al. (2007)).

The empirical model is defined as:

$$\begin{aligned}
 AsthmaHospitalization_{it} = & \beta_0 + \beta_1 PM2.5Concentration_{sit} + \beta_2 Precipitation_{it} \\
 & + \beta_3 SmokingRate_{it} + \beta_4 PopulationDensity_{it} + \beta_5 HispanicPopulation_{it} \\
 & + \theta WPM2.5Concentration_{jt} + \nu_i + \omega_t + \epsilon_{it}
 \end{aligned} \tag{3}$$

where *AsthmaHospitalization* stands for the asthma hospitalization number in county *i* and time *t*, *PM2.5 Concentrations* represents PM_{2.5} concentrations in county *i* and time *t*, *SmokingRate* is the smoking rate in county *i* and time *t*, *PopulationDensity* shows the population density in county *i* and time *t*, *Precipitation* shows the precipitation in county *i* and time *t*, *HispanicPopulation* is the percent of Hispanic population in county *i* and time *t*, while ν_i and ω_t are county and year fixed effects, respectively. With county fixed effects, there is not a need to control for the availability of hospitals in each county as the number of hospitals in each county does not change very much over time. The term *WPM2.5 concentrations* denotes the spatial components of PM_{2.5} concentrations. θ represents the spillover effects of PM_{2.5} concentrations. This coefficient explains the effects of PM_{2.5} concentrations of neighboring county (*j*) on the asthma hospitalization in county (*i*).

Elhorst (2014) notes that "for the specification of more complicated behavioral hypotheses, including effects" (time fixed effect, space fixed effect, and two-way fixed effect) (p. 2). Spatial

units have unique characteristics which are not always possible to control for all of them. Panel estimation introduces a dummy variable for spatial units in the estimation to capture unobservable predictors for units ν_i . Our model also controls for time fixed effects to capture unobservable predictors over time (ω_t).

6 Data

Data for constructing the empirical models come from different sources. The number of hospitalizations for asthma are derived from the National Environmental Public Health Tracking Program (NEPHTP) for 2001-2014 and classified using the International Classification of Diseases, ninth Revision (ICD-9). The data covers ICD-9-CM: 493.XX diagnosis codes. More asthma related indicators such as asthma prevalence among adults, asthma prevalence among children, and emergency department visits for asthma are reported, but only over a more limited number of years and states. By definition, hospitalization data does not include asthma among individuals who do not receive medical care or who have not been hospitalized, including those who die in emergency rooms, in nursing homes, or at home without being admitted to a hospital, and those treated in outpatient settings. NEPHTP provides asthma hospitalization information by counties for 28 selected states. Data are based on the date of admission rather than the date of discharge. Data represents the number of admissions rather than the number of individuals admitted to the hospital. In most cases, admissions of residents to out-of-state hospitals are excluded. Data are based on the county of individual residency.

For the independent variable of interest, we created a measurement of annual PM_{2.5} concentrations level based on data provided by CDC-NEPHTP. NEPHTP reports different air quality indicators, such as air toxics, mortality benefit associated with reducing PM_{2.5} concentrations level, and days above regulatory standard for Ozone and PM_{2.5}. PM_{2.5} concentrations levels are based on seasonal averages and daily measurement for monitor and modeled data. A Downscaler (DS) model is applied to predict the measurements for county and day observations with missing values in monitoring data. The data generation process in DS is based on statistical fusion of the Air Quality System (AQS) and Community Multiscale Air Quality (CMAQ) model-predicted concentration values. AQS was used for observations with monitoring data.

Population data come from the Bureau of Economic Analysis (BEA), while population breakdowns by race are provided by the National Bureau of Economic Research (NBER). Precipitation data are collected through PRISM climate group is supported by the USDA Risk Management Agency, and the National Center for Biotechnology Information published cigarette smoking prevalence in U.S. counties. Finally, for the spatial weight matrix, a shape file of Pennsylvania counties consisting of the latitudinal and longitudinal coordinates of all the 67 counties is adapted from the U.S. Census Bureau (Tiger) report.

Contiguity and neighborhoods in spatial analysis play vital roles (Tobler (1970)). To control for spillover effects of PM_{2.5} concentrations, 67 contiguous counties were included in our analysis. Wind map of the United States and World Forecast Directory, El Dorado Weather, Inc. are used to make the weight matrix. Descriptive statistics for each variable are reported in Table 1 along with the expected signs of PM_{2.5} concentrations and the control variables.

Our motivation to work with a spatial model in this analysis is based upon air pollution movement tied to geographical distance. One should expect to see the residence of downwind locations being affected by air pollution levels from upwind areas. Before we analyze the model in a spatial regression framework, we used an intuitive way to identify asthma hospitalization clusters. Figure 4 shows the map of asthma hospitalization for 2014, the last year of the dataset. Some spatial

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max	Expected sign of coefficient
Asthma Hospitalization (Number)	325.68	919.18	1	8,132	
PM2.5 Concentrations (μ/m^3)	12.23	2.42	7.8	23.3	+
Smoking Rate (%)	19.67	2.95	9.04	25.7	+
Precipitation (Inches)	46.03	8.54	24.73	83.86	+
Per Capita Income (Thousand dollars)	33,725	8,343	18,263	75,835	-
Population Density (Pop./mi ²)	446.87	1,330.46	12.04	10,911.16	+
Hispanic Population (Thousand People)	9,472	24,034	19	213,487	+
Hispanic Population 19 and below (Thousand People)	3,811	9,467	8	78,000	+
Number of observations	938				

clusters are obvious in 2014. Allegany county, Washington county and Westmorland county in the Southwest of the state had the highest category of asthma hospitalization. In addition, another cluster in the Southeast of the state followed the same pattern.

The next step after visualizing asthma hospitalization among counties is to detect spatial autocorrelation. To test for asthma hospitalization autocorrelation, we applied the 1st-order spatial autoregressive (FAR) estimates code written by James P. LeSage, available through the spatial econometrics Toolbox for Matlab. FAR output includes the rho coefficients that indicates the autocorrelation between a dependent variable and a dependent variable in surrounding neighbors.

Table 2 shows the results for the 1st-order spatial autoregressive estimates for two points of time and its z-probability. These tests reveal that there is a significant spatial autocorrelation among counties in Pennsylvania. This means that Pennsylvania asthma hospitalization numbers tend to be clustered together.

7 Results

The objective of this study is to investigate both the in-county and out-of-county effects of PM2.5 concentrations on asthma hospitalization. To be able to respond to this question by estimating a two-way fixed effect spatial panel model, we tested the null hypothesis that the spillover effects of PM2.5 concentrations is statistically different from zero. As discussed in the previous sections, finding an accurate algorithm to deal with the spillover between pollutants and asthma matters. The weight matrix which defines the neighbors based on wind direction was determined to be the most accurate algorithm to investigate spillover effects of the pollution. To do a placebo test and check the reliability of the model, we tried applying a different weight matrix by using the reverse prevailing wind direction and the results shows statistically insignificant indirect effects.

The estimated results for the model are reported in Table 3. The PM2.5 concentrations variable has a positive and significant coefficient, meaning that there is a positive, within county correlation between PM2.5 concentration and asthma hospitalization. A one microgram per cubic meter increase in PM2.5 concentrations is associated with approximately 27 more asthma hospitalizations within the county where this increased concentration occurs. The indirect effects of the PM2.5 concentrations are shown by the coefficient of PM2.5 concentrations in neighboring counties' variable (Table 3). This coefficient is positive and statistically significant, meaning that asthma hospitalizations increase with

Table 2: 1st-order spatial autoregressive Rho for Pennsylvania asthma hospitalization

	2001	2014
Rho	0.334	0.325
z-probability	0.027	0.032

increasing PM_{2.5} concentrations in upwind counties. A one microgram per cubic meter increase in PM_{2.5} concentrations in county i is associated with approximately 20 more asthma hospitalizations in downwind counties.

Other positive and statistically significant influences on asthma hospitalization include the percentage of smokers in a county, the density of the county’s population, and the number of Hispanics in the population. A 1% increase in smoking rate is associated with approximately 11 more asthma hospitalizations within a county, while the positive effects of higher population density and a greater Hispanic population are much smaller than smoking.

In addition to PM_{2.5} concentrations, the percentage of smokers in a county is another variable in our model that is alterable by public policy. While neither the health effects of smoking nor PM_{2.5} concentrations are limited to asthma prevalence (heart disease, stroke, cardiovascular disease, chronic obstructive pulmonary disease (COPD), and lung cancer increase with smoking), it is worth considering the comparative public health benefits from policies focusing on smoking rate reduction versus lowering of PM_{2.5} concentrations. We calculate the impacts of reducing both the smoking rate and PM_{2.5} concentrations by 10 percent from their current mean value over all counties. The results show that the effects of reducing PM_{2.5} concentrations on asthma hospitalization is more than 2.5 times higher than the impacts of reducing smoking rate (58 vs. 22 less hospitalizations). Since the constant term in a fixed effect panel estimate that includes both year and county fixed effects is essentially not interpretable, we provide no explanation for the constant in this model.

Finally, to check the consistency of the results, other population breakdown variables based on race, gender, and age are introduced into the model. The estimated results based upon these new control variables are reported in Table 4. The three new variables introduced into the model are: Hispanic population age 19 and below (Model 1), Hispanic female population (Model 2), and Hispanic female population age 19 and below (Model 3). The relative magnitude and the sign of the indirect effects of PM_{2.5} concentrations remains unchanged from Table 3. These results are consistent with other studies, such as Lwebuga-Mukasa et al. (2004) who found positive correlations between asthma and demographics such as the Hispanic population, the female population, and children 18 years old and under.

8 Conclusions and Policy Implications

The objective of this study is to understand the asthma related health impacts from PM_{2.5} concentrations. More specifically, the impact of PM_{2.5} concentrations on asthma hospitalization in Pennsylvania is investigated. A balanced panel of 67 counties in Pennsylvania over fourteen years (2001-2014) is applied to estimate the effects and capture the spillovers from PM_{2.5} concentrations across counties. In this research, we identify an important aspect missing in the health impact analysis literature of ambient air pollution - the presence of statistically significant spatial auto-

Figure 4: Asthma hospitalization in Pennsylvania counties 2014

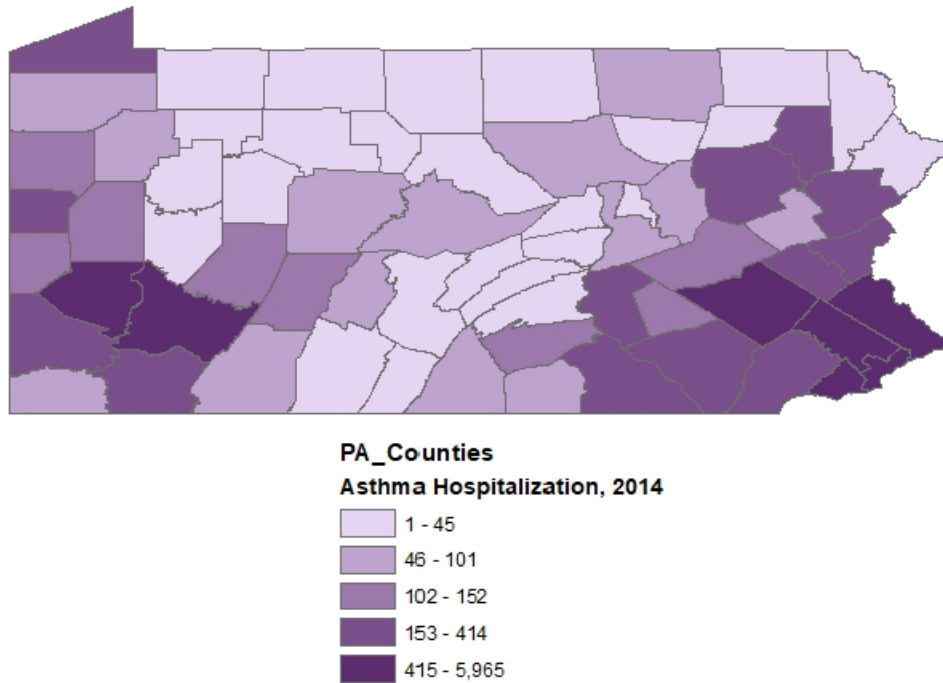


Table 3: Asthma hospitalization estimation results for the SLX model

Variable	SLX model
PM2.5 Concentrations	27.403*** (0.000)
Smoking Rate	11.262*** (0.006)
Precipitation	-0.695 (0.419)
Per Capita Income	1.793 (0.207)
Population Density	0.601*** (0.000)
Hispanic Population	3.483*** (0.000)
PM2.5 Concentrations in neighboring counties	19.980*** (0.000)
Constant	-806.779*** (0.000)
Year fixed effect	Yes
County fixed effect	Yes
Adjusted R-squared	0.94
Number of Observations	938

Note: Numbers in the parentheses represent P-values
*, **, and *** refer to 10% 5%, and 1% significance levels, respectively.

Table 4: Asthma hospitalization estimation results for the SLX model (robustness check)

Variable	Model 1	Model 2	Model 3
PM2.5 Concentrations	27.080*** (0.000)	27.582*** (0.000)	27.155*** (0.000)
Smoking Rate	11.025*** (0.007)	11.314*** (0.005)	11.116*** (0.006)
Precipitation	-0.685 (0.426)	-0.698 (0.417)	-0.686 (0.426)
Per Capita Income	1.807 (0.204)	1.953 (0.170)	1.856 (0.192)
Population Density	0.607*** (0.000)	0.600*** (0.000)	0.606*** (0.000)
Hispanic Population 19 and below	8.043*** (0.000)	-	-
Hispanic Female Population	-	7.049*** (0.000)	-
Hispanic Female Population 19 and below	-	-	16.836*** (0.000)
PM2.5 Concentrations in neighboring counties	19.963*** (0.000)	19.865*** (0.000)	19.955*** (0.000)
Constant	-799.220*** (0.000)	-812.815*** (0.000)	-803.308*** (0.000)
Year fixed effect	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Adjusted R-squared	0.94	0.94	0.94
Number of observations	938	938	938

Numbers in the parentheses represent P- values

*, **, and *** refer to 10% 5%, and 1% significance levels, respectively.

correlation among the number of county level asthma hospitalizations. This presence implies that the ordinary least square estimations (non-spatial models) may lead to a biased result and underestimate the overall impact of PM_{2.5} concentrations on asthma hospitalization. Spatial models incorporate the intercorrelation between county level PM_{2.5} concentrations and thereby capture the spillover effects of these concentrations. In addition, applying spatial analysis without correctly employing wind direction to identify each unit's neighbors also generates inaccurate estimations of PM_{2.5} concentrations impacts. Putting into practice the proper upwind and downwind relationships between counties within an ambient air pollution impact assessment is a key element to derive a precise impact estimations.

Our results suggest that county level PM_{2.5} concentration is important explanatory factor in asthma hospitalization. This finding is similar to the findings of numerous studies, including Glad et al. (2012), Mann et al. (2010), Meng et al. (2010), Liu et al. (2008), Jacquemin et al. (2012), Malig et al. (2013), Samoli et al. (2011), and Silverman and Ito (2010). While there are several GIS-based studies focused on the locational impacts of asthma (Yap et al. (2013); Crighton et al. (2012); Hanchette et al. (2011)), the asthma hospitalization impacts from PM_{2.5} concentrations occurring in upwind counties have not been discussed in the literature before.

This study shows one-unit increase in PM_{2.5} concentrations is associated with 47 more asthma hospitalizations within both the county and in downwind counties. Considering the average charge for inpatient hospitalization in Pennsylvania (\$26,952), the total annual cost of one unit increase in PM_{2.5} concentrations in one county in Pennsylvania involving asthma hospitalization is on average \$1.29M (\$754,656 direct and \$539,040 indirect). Thus, ambient air pollution represents a regional issue rather than one related specifically to attainment or non-attainment of air quality standards at the county level.

There is a wide range of asthma hospitalizations across Pennsylvania counties. For example, in 2014 there were four counties with less than 10 reported asthma hospitalizations and, at the same time, the upper bound of asthma hospitalization among Pennsylvania counties was more than 5,000. Thus, since our direct and indirect estimates reflect average effects of PM_{2.5} concentrations across all counties, they probably are more reflective of urban/suburban counties rather than rural counties with small population size.

This study's findings have policy implications for both federal and local governments. In December 2012, EPA reduced PM pollution standards by tightening the annual PM_{2.5} standard from 15 to 12 μ/m^3 . Even small changes at lowering the standard could have significant impacts on public health. Giannadaki et al. (2016) note that governments continue to adopt stricter limits for annual mean PM_{2.5} level. As shown in this research, lower limits for PM_{2.5} concentrations lead to substantial reductions in at least one negative human health outcome - asthma hospitalizations.

Although ambient air pollution has gained more attention for many years and there has been implementation of many regulations and air quality standards to help control pollution levels, still more work needs to be done. As one example, if the existing method to calculate the PM_{2.5}-attributable health effects is not capturing the spillover effects, this study recommends the inclusion of the out of area health effects of PM_{2.5} concentrations in the consideration of setting or revising primary PM standards. Because the regulation of pollutants is an economic burden for the power generation sector and society in general (Curtis (2018)), the most accurate accounting of human health effects is needed when considering pollution standard reductions - i.e. those which incorporate spillovers effects. Since nonattainment designations along with their incumbent increased regulation on pollution dischargers happen at city and county levels, the spillover benefits from these additional regulations need to be considered as the human health impacts of air pollution knows no boundaries.

Several limitations in the research are recognized. First, to account for wind patterns, future research should consider a more detailed algorithm that involves wind speed and wind rose when

computing a weight matrix. Wind rose is a diagram that shows the relative frequency of wind direction in a particular place. In practice, wind direction and speed change over time, so to investigate the effects of ambient air pollution, one needs to continually adjust the neighbors according to the frequency of wind direction and speed. For this research, corresponding information about direction and speed were not available for each county and each year. Thus, the empirical results found here may change with more accurate data of wind patterns.

Second, asthma hospitalization is currently the only data available at the county level for Pennsylvania. Access to asthma prevalence and asthma emergency department visits data for conducting new estimations using these asthma related incidents would provide researchers with a better estimation of PM_{2.5} impacts. Finally, expanding the study region by applying all U.S. counties will provide a better understanding of the health impacts of the pollution. Unfortunately, data for all the counties in the U.S. are not available in this point. Having access to these point data pollution levels may enable the researchers to achieve results that are more accurate. Unfortunately, the pollution data for points in county level in a time series is not readily available. One would expect point source data on pollution show greater effects on asthma hospitalization.

Further research should consider improving on the above limitations by imposing a more accurate wind pattern, expanding estimations to include emergency department visits and asthma prevalence, and a county level analysis on the national level are recommended for future works. The current outcome does contribute to the literature by examining the impact of ambient air pollution on human health by specifically documenting and estimating the cost of asthma spillover effects across Pennsylvania counties from PM_{2.5} concentrations.

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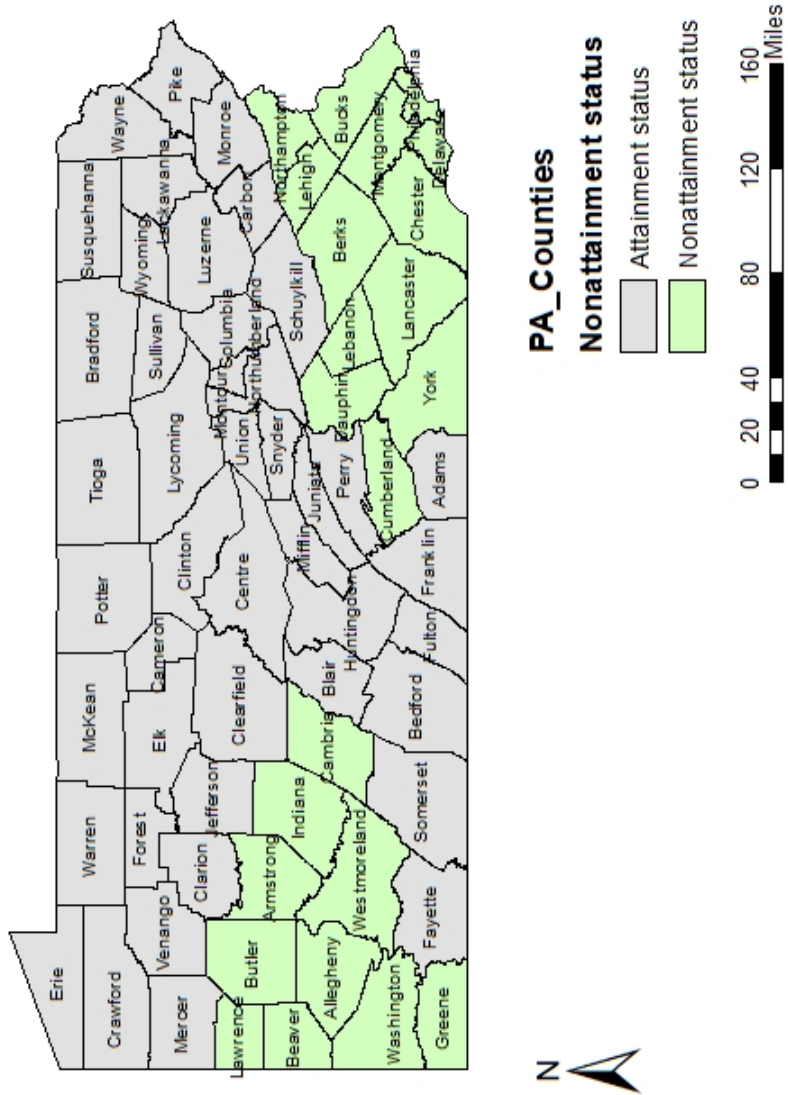
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Figure 5: Appendix I. Attainment vs. nonattainment designation status in Pennsylvania counties based on PM2.5 concentrations criteria.



Note: Using the data from EPA Green Book, National Area and County-Level Pollutant Information, we define attainment vs. nonattainment counties based on the PM2.5 concentrations criteria. If the county falls in a nonattainment status in any years between 2001 and 2014, we consider it a nonattainment county, otherwise the county falls in an attainment status.