Air Quality and Asthma Hospitalization Rates: 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, including approximately 25 million in the United States. There is substantial epidemiological evidence particulate matter concentrations and asthma. Based upon county level data from 2001-2014, a spatial panel framework with weights based upon prevailing wind patterns is used to investigate the direct and indirect impacts of $PM_{2.5}$ concentration levels on asthma hospitalization rates in Pennsylvania. This model controls for population density, precipitation, per capita income, and smoking rate. Results show that $PM_{2.5}$ concentrations have positive effects on asthma hospitalization rates (both direct and indirect). For example, a one μ/m^3 increase in $PM_{2.5}$ concentrations throughout all counties in Pennsylvania raises the number of annual asthma hospitalizations by over 400, with 53.8% of this increase occurring due to spillover effects. This study highlights the need for a more accurate impact analysis of ambient air pollution on asthma that reflects the impacts of both local and neighboring regions' air quality. In the case of asthma hospitalization rates from $PM_{2.5}$ pollutions, an appropriate wind direction algorithm also is important to identify spillover effects across counties.

1 Introduction

Ambient air pollution adversely impacts air quality and human health (Nel, 2005; Kampa and Castanas, 2008; Anderson et al., 2012). The national average trend of SO_2 air quality shows an 87% decrease between 1980-2016 (Environmental Protection Agency, 2016b). With decreasing trends in SO_2, 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, 2018). 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).

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 non-attainment by an area. Attainment/ non-attainment 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 non-attainment area deals with persistent air quality problems and violates federal health-related standards for outdoor quality (Pennsylvania Department of Environmental Protection, 2016).

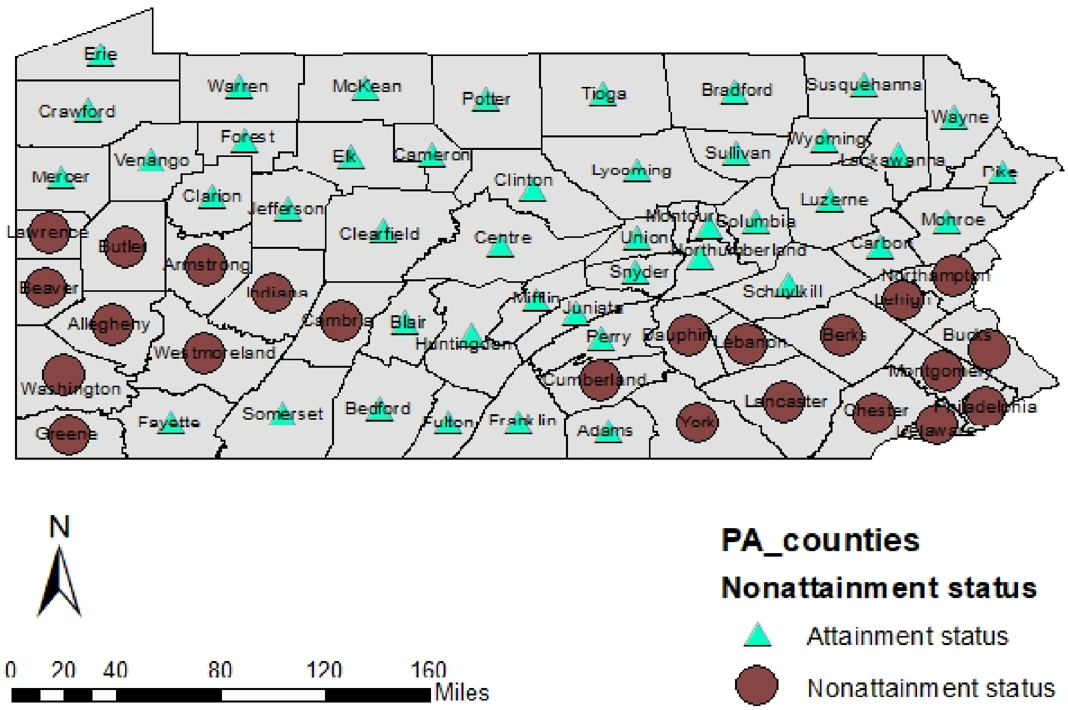

Figure 1: Attainment vs. non-attainment designation status by county Pennsylvania based on PM2.5 concentrations criteria between 2001 and 2014.
Note: Using the data from EPA Green Book, National Area and County-Level Multi-Pollutant Information, we define attainment vs. non-attainment counties based on the PM2.5 concentrations criteria. If the county falls in a non-attainment status in any years between 2001 and 2014, we consider it a non-attainment county, otherwise the county falls in an attainment status.

As a demonstration, Figure 1 shows non-attainment designation for PM2.5 concentrations in Pennsylvania are located primarily at or adjacent to metropolitan areas in the southeast and southwestern portions of the state. Pollution dischargers within non-attainment areas are required to comply with tighter environmental regulations than similar dischargers in attainment areas. For instance, in non-attainment 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 PM2.5 concentrations, explain asthma hospitalization rates in Pennsylvania. Applying a spatial regression model, this analysis provides us with estimates of both within county and spillover effects among contiguous counties from PM2.5 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 PM2.5 concentrations. To the best of our knowledge, spillover analysis of PM2.5 pollutions is missing in public health literature. This study aims to address this gap in the literature.

Spatial connections between counties are created by imposing prevailing wind patterns to determine neighbor and non-neighbor interactions. The results of a spatial econometric model reveal that county PM2.5 concentrations are associated with both higher asthma hospitalization rates within the county itself (a positive direct effect) along with increased hospitalization in neighboring, downwind counties (a positive indirect effect). Thus, important spillover effects exist from the PM2.5 concentrations on asthma hospitalization rates.

The main contribution of this research to the literature is investigating the spillover effects of the sources of PM2.5 pollutions on asthma hospitalization rates. In addition, the study introduces a new approach to evaluating who is considered a neighbor regions based upon prevailing wind direction. After examining the literature, no previous study has controlled for this type of spatial interaction between PM2.5 concentrations and asthma hospitalization rates, so that the regional aspects of PM2.5 concentrations have not been investigated. Since PM2.5 and other air pollutant concentrations move through the atmosphere, 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, PM2.5 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 (Centers for Disease Control and Prevention, 2013). Being exposed to multiple environmental factors exacerbate asthma symptoms. Akinbami et al. (2011), and Akinbami et al. (2012) list airway irritants such as tobacco smoke and air pollution, allergens, respiratory infections, stress and exercise among common asthma attach triggers that exacerbate symptoms.

2.1 National and state asthma trend, and the burdensome cost of asthma on society

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). 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). 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. Florida, Alabama, Pennsylvania, and Utah are among the high increase states for adult asthma prevalence. Compared to the average percentage increase in the U.S. between 2001-2015 (43%), Pennsylvania experienced a slightly higher increase rate at 47%.

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).

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" (Environmental Protection Agency, 2016a) (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).

The most recent estimates for the annual economic cost of asthma in the U.S. shows an increase from $12 billion (equivalent to about $28 billion in 2019) in 1994 to $56 billion (equivalent to about $69 billion) in 2011 (National Hospital Ambulatory Medical Care Survey, 2011; National Hospital Ambulatory Medical Care Survey, 2011). The cost involving asthma hospitalization in Pennsylvania follows the same increasing trend over the years (Pennsylvania Department of Health, 2012). In the next section, the connection between ambient air pollution and PM2.5 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 Balmes, 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.

The negative effects of PM2.5 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 PM2.5 (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 μ/m^3 in PM2.5 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 μ/m^3 for PM2.5 leads to an average loss of life expectancy between 9 and 11 years (Andersen, 2017). One of the issues with PM2.5 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).

In a study done by the Schneider et al. (2010), estimates for the health impacts of PM2.5 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 PM2.5 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.

In Lipsett et al. (1997), the authors show the relationship between emergency room visits and exposure to PM10 in Santa Clara County, California during the winters of 1988-1989 through 1991-1992. A time-series analyses using Poisson regression was applied and the results indicate a consistent relationship between the number of ER visits and PM10. In addition, Liu et al. (2008) conducted a study on 182 children with asthma, ages 9 to 14 over a 4-week period between October and December of 2005 in Windsor, Ontario, Canada. Using mixed-effects regression models and adjusting for confounding variables, their results indicate that the air pollution may increase airway oxidative stress and decrease small airway function of asthmatic children.

Another study by Mann et al. (2010) choose 315, 6-11 years old children with asthma in Fresno, California between November 2000 and April 2005. The authors applied statistical analysis and time series estimations to find that boys with mild intermittent asthma exposed to PM2.5 had increased risk of wheeze. Meng et al. (2010) surveyed 1,502 individuals in the San Joaquin Valley, California for daily or weekly asthma symptoms and asthma-related ED visits or hospitalization in the past year. The statistical analysis applied adjusting for age, gender, race/ethnicity, poverty level and insurance status. The results indicate that individuals exposed to higher level of PM2.5 are more likely to have asthma symptoms and ED/hospital visits.

In addition to Mann et al. (2010) and Meng et al. (2010) studies, Silverman and Ito (2010) describe the effects of PM2.5 on asthma symptoms by using a daily time-series analysis of 6,008 asthma ICU admissions and 69,375 general (non-ICU) asthma admissions in New York City hospitals from April to August over the 1999 to 2006 time period. The results show children with asthma are affected by particulate matter.

In the northern portion of the United Kingdom, Namdeo et al. (2011) conducted a time series analysis to capture the effects of PM on respiratory hospital admissions (and mortality) mainly among the elderly population between April 2002 and December 2005. The results indicated that PM10 is positively associated with respiratory hospital admissions. Conducting research the short-term effects of particulate matter on pediatric asthma emergency admissions in Athens, Greece over the period 2001-2004 is a study by Samoli et al. (2011). These authors use daily time-series data provided by children's hospitals and fixed pollution monitoring stations. Results from Poisson regression models confirm that exposure to PM10 increases emergency hospital admissions for pediatric asthma.

Glad et al. (2012) gathered data from 2002 to 2005 for individuals with a primary discharge diagnosis of asthma presented to 1 of 6 EDs in Pittsburgh, Pennsylvania. The authors apply a case-crossover methodology to be able to control for the effects of subject-specific covariates such as gender and race. Their results indicate that exposure to PM2.5 has an effect on African American populations. In another study, by linking residential address of 481 subjects with current asthma and using a 4 km grid air pollutant surface developed by the French Institute of Environment, Jacquemin et al. (2012) apply multinomial and ordinal logistic regressions and find that long term exposure to PM_{10} is associated with uncontrolled asthma in adults.

In a review article, Ristovski et al. (2012) examine research on the health effects of diesel particulate matter by adopting a two-step research methodology: (1) characterizing the physico-chemical properties of diesel PM (DPM), and (2) relating specific DPM constituents to inflammation, innate and acquired immunity, and oxidative stress. Malig et al. (2013) study the relationship between coarse particles and respiratory emergency department visits from 2005 to 2008 within 35 California counties. A time-stratified case-crossover design is applied to control for time-invariant confounders and seasonal influences. The result shows coarse particle exposure may trigger asthma exacerbations.

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 $PM_{2.5}$ pollutions. 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). Delaware, Philadelphia, Montgomery, Bucks, and Washington are the counties with the highest asthma hospitalization rate, while Mifflin, Snyder, Juniata, Clinton, and Huntington counties have the lowest number of asthma hospitalizations. What the counties with a high asthma hospitalization rate and counties with a low asthma hospitalization rate have in common is their population density. Counties with a higher population density are struggling with more asthma triggers than counties with lower asthma hospitalization rate, which are usually more rural.

5 Models

A spatial regression model is used to investigate the impacts of $PM_{2.5}$ concentrations on asthma hospitalization rates. 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 dependent variable for each observational unit depends on an independent variable from other units of observations.

$$Independent variable x of unit\ j \longrightarrow Dependent variable y of unit\ i \tag{1}$$

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 × 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 PM_{10} 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 PM_{10} concentrations, respectively. These authors argue that for some cases, such as network data and PM_{10} 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).

Using El Dorado Weather, Inc. map, the prevailing wind direction in Pennsylvania was determined to be southwest to northeast. According to this prevailing wind direction, for instance, Washington County, in the southwest portion of Pennsylvania, is a neighbor of Allegheny and Westmoreland Counties. However, being down wind, both Allegheny and Westmoreland Counties are not neighbors for Washington County. In addition, 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)).

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) and per capita income (Kozyrsky et al., 2010). Each control variable is expected to be positively correlated with asthma incidence. While per capita income level has been shown to be negatively correlated with asthma incidence (Kozyrsky et al., 2010), asthma hospitalization rate is utilized here which leads us to believe that as per capita income declines, there are more low-income households in a county that may not have enough financial resources nor health insurance to afford to visit a hospital when breathing difficulties arise For this reason, our expectation for the impact of a per capita income variable on hospitalization rate is different from those in the literature. Finally, 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:

$$\begin{aligned} AsthmaHospitalization_{it} = \beta_0 + \beta_1 PM2.5Concenterations_{it} + \beta_2 Precipitation_{it} \\ +\beta_3 PerCapitaIncome_{it} + \beta_4 SmokingRate_{it} + \beta_5 PopulationDensity_{it} + \beta_6 HispanicPopulation_{it} \\ +\theta WPM2.5Concenterations_{jt} + \nu_i + \omega t + \epsilon_{it} \end{aligned} \quad (3)$$

where *AsthmaHospitalization* stands for the asthma hospitalization number in county i and time t, *PM2.5 Concenterations* represents PM2.5 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. 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 these characteristics. 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). Given the use of county fixed effects, there should be no need to control for other factors, such as the availability of hospitals in each county, which do not change very much over time. The term WPM2.5concenterations denotes the spatial components of PM2.5 concentrations. θ represents the spillover effects of PM2.5 concentrations. This coefficient explains the effects of PM2.5 concentrations of neighboring county (j) on the asthma hospitalization rate in county (i).

6 Data

Data for constructing the empirical models come from different sources. The rate 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). We work with age-adjusted hospitalization rate. 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 PM2.5 concentrations level based on data provided by CDC-NEPHTP. NEPHTP reports different air quality indicators, such as air toxics, mortality benefit associated with reducing PM2.5 concentrations level, and days above regulatory standard for Ozone and PM2.5. PM2.5 concentrations levels are based on seasonal averages and daily measurement for monitor and modeled data. A Downscaler (DS) model is applied by the U.S. Environmental Protection Agency (EPA) 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). 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 PM2.5 concentrations, 67 contiguous counties were included in our analysis. Wind map of the

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max	Expected sign of coefficient
Asthma Hospitalization age-adjusted rate (per 10,000)	12.51	4.78	4.6	32	
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./mi2)	446.87	1,330.46	12.04	10,911.16	+
Hispanic Population % (expressed as a decimal)	0.030	0.035	0.003	0.216	+
Number of observations			938		

Table 2: Results of 1st-order spatial autoregressive rho calculations for county level asthma hospitalization rates in Pennsylvania (age adjusted rates)

	2001	2014
Rho	0.961	0.980
z-probability	0.000	0.000

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 PM2.5 concentrations and the control variables. Aside from the descriptive statistics for all the observations, we compare descriptive statistics for attainment and non-attainment counties. Asthma hospitalization rate and PM2.5 concentrations are very different in attainment vs. non-attainment counties.

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 rate clusters. Figure 2 shows a map of asthma hospitalization rates for 2014, the last year of the dataset. Some spatial clusters are obvious in 2014. Philadelphia, Montgomery, Delaware and Bucks counties in the southeastern part of the state all had asthma hospitalization rates in the highest category. In addition, there is another cluster of high category rates in the southwest part of the state. Each cluster is associated with a metropolitan area (either Philadelphia and Pittsburgh).

The next step after visualizing asthma hospitalization among counties is to detect spatial autocorrelation. To test for asthma hospitalization rate 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 are significant spatial autocorrelations among counties in Pennsylvania. This means that Pennsylvania asthma hospitalization rates tend to be clustered together.

7 Results

Both the in-county and out-of-county spillover effects of PM2.5 concentrations on asthma hospitalization are examined by estimating a two-way fixed effect spatial panel model. We test the null hypothesis that the

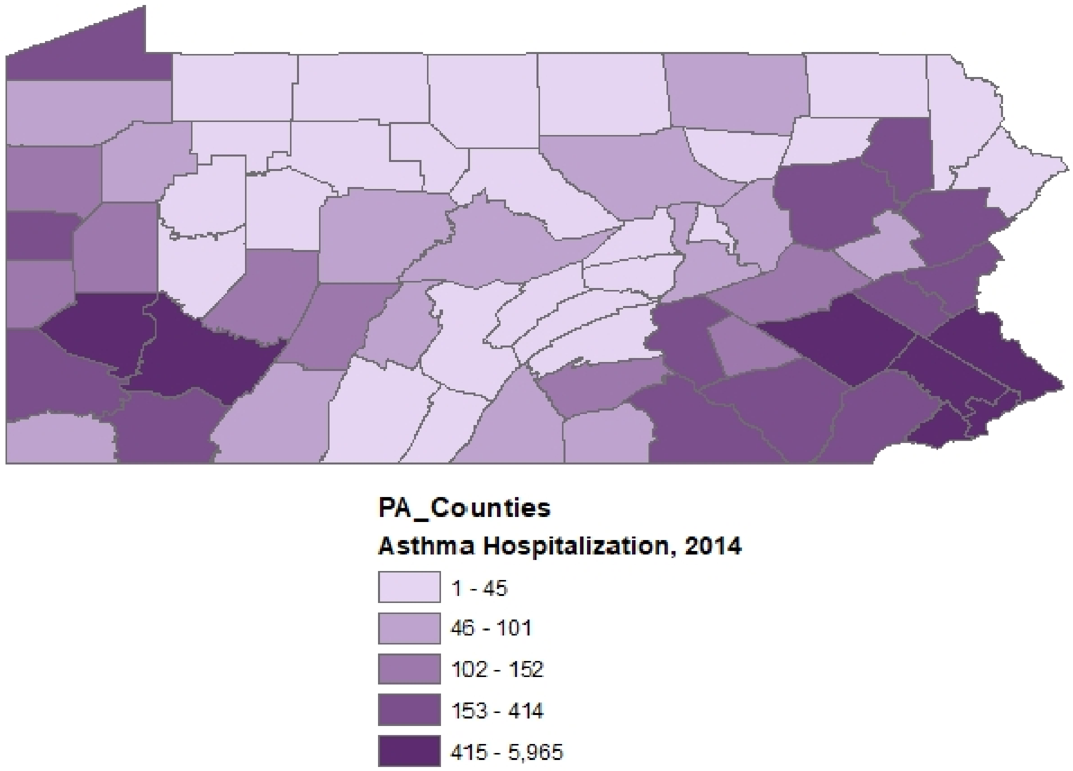

Figure 2: Asthma hospitalization rates in Pennsylvania counties, 2014 data

spillover effects of PM2.5 concentrations are statistically different from zero. To be capable of comparing the results with a model without controlling for spillover effects, we report the OLS estimation that excludes any spillover effects of PM2.5 concentrations. The joint effects (direct and indirect) in the spatial model are larger than the direct effect in OLS model, while the source of the effects is different in two models. The OLS model ignores the out of county effects assuming all the effects of PM2.5. on asthma hospitalization in county "j" raised by PM2.5 in county "j". Unlike PM10, PM2.5 is a fine particle, which can travel further than PM10. Our analysis is based on the assumption that unlike PM10 concentrations, which will diminish considerably as the distance between neighbors increases, PM2.5 concentrations will diminish with a lower rate as the distance between neighbors increases. 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. We also tested to see whether the means of asthma hospitalization rate vary between attainment and non-attainment counties. The result of the t-test shows the mean of asthma hospitalization is statistically different in attainment vs. non-attainment counties (t-stat = 18.76, attainment counties' mean = 10.71, non-attainment counties' mean = 15.97).

The estimated results are reported in Table 3. In both models, 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 rates. A one μ/m^3 increase in PM2.5 concentrations is associated with an estimated 0.128 per 10,000 population increase in the asthma hospitalization rate within the county where this increased concentration occurs. The indirect effects of 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 at the 10% level, meaning that asthma hospitalization rates increase with increasing PM2.5 concentrations in upwind counties. A one μ/m^3 increase in PM2.5 concentrations in county i is associated with an estimated 0.154 per 10,000 higher rate of asthma hospitalizations in downwind counties.

Other positive and statistically significant influences on asthma hospitalization include population density,

Table 3: Asthma hospitalization estimation results for the OLS and the SLX model

Variable	OLS model (age-adjusted rate)	SLX model (age-adjusted rate)
PM2.5 Concentrations	0.210***	0.128***
	(0.060)	(0.074)
Precipitation	-0.008	-0.008
	(0.009)	(0.009)
Per Capita Income	0.1***	0.1***
	(0.02)	(0.02)
Smoking Rate	0.063	0.060
	(0.051)	(0.051)
Population Density	0.003*	0.003*
	(0.001)	(0.001)
Hispanic population %	18.225***	19.753***
	(4.889)	(4.952)
PM2.5 Concentrations in neighboring counties	-	0.154***
		(0.083)
Year fixed effect	Yes	Yes
County fixed effect	Yes	Yes
Adjusted R-squared	0.96	0.96
Number of observations	938	938

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

per capita income, and Hispanic population percentage. 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.[1]

8 Conclusions and policy implications

The objective of this study is to understand the asthma related health impacts from PM2.5 concentrations. More specifically, the impacts of both in-county and neighboring county PM2.5 concentrations on asthma hospitalization rates in Pennsylvania are 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 PM2.5 concentrations on asthma hospitalization rates 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 autocorrelation among county level asthma hospitalization rates. This presence implies that the ordinary least square estimations (non-spatial models) may lead to a biased result and underestimate the overall impact of PM2.5 concentrations on asthma hospitalization rates. Spatial models incorporate the intercorrelation between county level PM2.5 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 PM2.5 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 estimation.

Our results suggest that county level PM2.5 concentration is an important explanatory factor in asthma hospitalization rates. This finding is similar to the ndings 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), asthma hospitalization impacts from PM2.5 concentrations occurring in upwind counties have not previously been discussed in the literature.

From Table 3 results, a one μ/m^3 increase in PM2.5 concentrations is associated with a combined asthma

[1] We also estimate a separate model to include county specific time trends to see if time trend for counties follow the same pattern. Most of the counties follow a negative time trend.

hospitalization rate increase of 0.28 per 10,000 population within both the county itself where the increase occurs as well as in downwind counties. 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 PM2.5 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 PM2.5 level. As shown in this research, lower limits for PM2.5 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 PM2.5-attributable health effects is not capturing the spillover effects, the findings from this study show that inclusion of the out of area health effects of PM2.5 concentrations are potentially important 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 non-attainment 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 spread beyond regulated areas.

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. The weak statistically significant indirect effect of PM2.5 concentrations could be an indicator showing that this analysis might benefit from generating a more precise wind direction weight matrix.

In addition to incorporating a more precise wind speed and direction weight matrix, we are aware that the impact of out-of-state effects is not captured in this analysis. Downwind counties located on the border with states of Ohio and West Virginia, are affected pollution concentrations of adjacent counties in neighboring states. While we are well informed of this effect, being adjacent county "j" in a neighboring state is a time invariant characteristic for county "i" border county in Pennsylvania. For this reason, we did to include a binary variable to control for any border effect that may exist because it would be dropped when the fixed effects models are estimated.

A third limitation is that asthma hospitalization data are currently only available at the county level for the state of Pennsylvania. Access to asthma prevalence and asthma emergency department visits data for conducting new estimations using asthma related incidents would provide researchers with a better estimation of PM2.5 impacts. Also, we are aware that household locational decisions may be affected by pollution concentration. It is possible that households with asthma patients may choose to live within areas of Pennsylvania with lower pollution concentrations in response to this condition. Given the current design of the study, we are unable to control for this fact. However, if households with members that suffer from asthma are going to move as a result of this condition, they are as likely to move out-of-state to a warmer climate as somewhere in the state of Pennsylvania.[2],[3]

As a final limitation, 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 at this point in time. 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 to show greater effects on asthma hospitalization.

Further research should consider improving on the above limitations by imposing a more accurate wind

[2]For more information, refer to: https://www.aafa.org/asthma-capitals-top-100-cities-ranking/
[3]For more information, refer to: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3519344/

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. Considering the limitations for the study, the current out-of-county PM2.5 impacts can be viewed as a lower bound effect. 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 PM2.5 concentrations.

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.

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