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Asthma Medication Use and Air Pollution In California: A Cross-Sectional Analysis

Charles Griffiths, Nathalie Simon and Tracey Woodruff

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U.S. Environmental Protection Agency
National Center for Environmental Economics
1200 Pennsylvania Avenue, NW (MC 1809)
Washington, DC 20460
http://www.epa.gov/economics

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Charles Griffiths and Nathalie B. Simon[1]
U.S. Environmental Protection Agency
National Center for Environmental Economics

Tracey Woodruff
University of California, San Francisco

Abstract:

In this study, we examine the effects of chronic exposure to air pollution on asthma exacerbation through a cross-sectional analysis of asthma prescriptions for quick-relief medications at the 5 digit zip code level in California. Using information on the use of maintenance therapies by each patient, we are able to stratify our data by asthma severity as well as by age. In general, we find a positive relationship between asthma and both PM_{10} and ozone levels. We find that prescriptions for quick-acting inhalers for children increases with PM_{10}, and this relationship generally does not level off effect except for mild intermittent asthmatics. Ozone also generally increases the number of prescriptions for ages 5 through17, as well as for severe asthmatics and some moderate asthmatics at younger ages. However, prescriptions and ozone show the opposite relationship for the adults and the very young (ages 0-4).

Key Words: Asthma, Air pollution

Subject Area Classifications: Ambient Air Quality, Risk Assessment, Children's Health

Corresponding Author:
Nathalie Simon
National Center for Environmental Economics
USEPA, Mail Code 1809T
1200 Pennsylvania Avenue, NW
Washington, DC 20460

[1] The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Environmental Protection Agency.

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Charles Griffiths, Nathalie B. Simon, Tracey Woodruff[2]
U.S. Environmental Protection Agency, National Center for Environmental Economics

Introduction

According to the American Lung Association, asthma is the leading serious chronic disease among children in the U.S. with over 6.8 million children under the age of 18 with the disease in 2006 (American Lung Association 2008). Characterized by inflammation of the airways, asthma results in intermittent, recurring episodes of wheezing, breathlessness, tightness of the chest, and coughing and often leads to hospitalization, ER visits and sometimes death. While the causes of asthma are still under investigation, asthma attacks can be triggered by exposure to allergens, strong fumes, respiratory infections, exercise, dry or cold air, as well as exposure to air pollution -- including ozone and particulate matter (PM). In fact, EPA recently tightened the standards for both pollutants based in part on evidence concluding that reducing exposure to these pollutants would result in fewer asthma attacks (US EPA 2008, US EPA 2006).

Relationships between short-term exposures to ambient air pollution and a variety of asthma-related outcomes have been explored in the literature. A number of daily time-series studies have found positive associations between short-term exposures to ambient air pollution (both ozone and PM) and asthma-related ER visits and hospitalizations as well as mortality. However, these studies only reflect outcomes experienced by a small

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segment of the population and are silent about the effects on less-severe outcomes or on effects of chronic exposure.

Some diary studies focus on the effects of short-term exposures on less-severe asthma outcomes such as reduced forced expiratory volume, reduced peak expiratory flow (PEF), other asthma symptoms or changes in asthma medication use. However, these studies face several difficulties including the fact that daily symptom rates are often highly correlated from one day to the next and the heterogeneity among subjects causes dependencies in the data (Schwartz et al. 1991). In addition, since these studies tend to have relatively short study periods (often less than 1 year), they generally provide little if any indication of the effects of chronic exposure to air pollution on asthma symptoms.

This study differs from these others in several important ways. First, we examine the effects of chronic exposure to air pollution on asthma exacerbation through a cross-sectional analysis conducted at the 5 digit zip code level in California. Similar to the diary studies, we focus on the effects of exposure to air pollution on a less severe morbidity outcome – use of short-term "quick relief" asthma medication; however, we are able to stratify our data not only by age but by several classes of asthma severity based on use of maintenance therapies.

Background

Longitudinal diary studies that consider asthma medication use generally fall into one of two categories (with some overlap) – those that specifically consider the use of quick relief asthma medication as an outcome of interest and those that focus on other outcomes but control for the effects of the use of asthma maintenance therapies. In a study of 53 adult asthmatics in Erfurt, Germany, von Klot et al. (2002) find that the use of β-agonists was associated with 5-day means of both fine and ultrafine particles while corticosteroid use was associated with cumulative exposures over 14 days to these pollutants. Gent et al. (2003) find a positive association between ambient exposures to both ozone and $PM_{2.5}$ and rescue medication use among children using maintenance medications in their study of 271 children younger than 12 years of age living in Southern New England. No such association was found for children not taking the maintenance therapies. Delfino, et al. (2002) find stronger associations between exposures to PM and asthma symptoms among children who were not taking anti-inflammatory medications in their daily panel study of 22 asthmatic children in a semi-rural area of southern California, with stronger associations noted among those children with respiratory infections. Lewis et al. (2005) consider the effects of ambient PM and ozone levels on lung function among 86 asthmatic children in Detroit, Michigan and find associations between higher exposures to these pollutants and poorer lung function among those children using corticosteroids compared to those who did not. Jalaludin, O'Toole and Leeder (2003), on the other hand, do not find any association between exposures to ambient levels of PM_{10}, ozone or NO_2 and asthma medication use in their study of 125 primary school children with a history of wheeze in metropolitan Sydney, Australia. None of these studies, however, consider the effects of long-term exposures to ambient air pollution levels on asthma symptoms.

Several studies have noted an association between exposures to air pollution and increased medication use and drug sales. Zeghoun et al. (1999) and Pitard et al. (2004) use a daily time series model to examine the relationship between respiratory drug sales in Le Havre and Rouen, France, respectively. Both studies find a positive association between respiratory drug sales and air pollution concentrations, indicating that data of this kind could be useful for future surveillance studies of the effects of air pollution exposure. This position is further supported by Naurekas et al. (2005) who, using claims data for recipients covered under Illinois Medicaid, specifically examine whether prescription fills for short-term β-agonists (or rescue medications) are a good marker for asthma morbidity. They find a strong and significant relationship between prescription fills and other morbidity endpoints – specifically emergency room visits and hospital admissions for asthma. Again, these studies focus on the effects of short-term exposures to ambient air pollution.

One recent study by Moore et al. (2008) does consider the consequences of long-term exposure to ozone by considering effects of exposure on hospitalizations for asthma among children in Southern California. Looking at hospital discharge data and ambient air pollution levels over 18 years across 195 10x10 km spatial grids, they find that ozone levels contribute to an increased risk in hospitalization of children with asthma even after controlling for a variety of demographic and weather variables.

Our study complements these studies by examining the effect of longer term or chronic exposures to air pollution on asthma symptoms as measured by the purchase of quick relief asthma medications across the state of California. We hypothesize that chronic exposure to air pollution may make an individual more susceptible to asthma attacks, causing an increase in the use of quick relief medications. Rather than consider the effects of daily increases in air pollution levels, this study focuses on differences in quarterly average pollution levels across zip codes and the effect of these observed differences on the purchase of quick relief asthma medications. Using prescription histories for each patient, we are able to stratify the prescription sales by the level of asthma severity experienced by the patient to account for effect modification of the maintenance therapies.

Model

Specifically, we model the effects of differences in long-term or chronic air pollution exposures on the occurrence of asthma attacks, where asthma attacks are proxied by the number of prescriptions for quick relief asthma medication. We assume a standard household production model in which individuals maximize a utility function:

$$U(x; A(c(o, f, s), q; z, l)) \text{ subject to } y = px + rq + wt \tag{1}$$

where p, the price of composite good x, can be set to one for convenience. Incidence of asthma attacks, A, is influenced by ambient conditions, c, which include ambient levels of air pollution, o, temperature, f, and season, s, as well as individual characteristics, z, and location characteristics, l. Asthma attacks can be mitigated through the use of quick-acting inhalers, q, at a cost of r. y is the individual's full-time income; w is the wage rate and t is leisure time.

Solving for the first order conditions for *q* produces:

$$\left(\frac{\partial U}{\partial A}\right)\left(\frac{\partial A}{\partial q}\right) \leq \delta \cdot r, \tag{2}$$

where δ is the Lagrange multiplier of the full income budget constraint. The inhaler is used to mitigate asthma symptoms until the benefit of doing so is less than or equal to the full marginal cost. If the rescue medication could be taken in a continuous fashion, then equation (2) could hold with equality. However, inhalers distribute the medicine in discrete, metered doses ("puffs"). Furthermore, in our case, asthma is an unobservable variable that is witnessed through the latent variable of the inhaler used. Thus, we only know that the inhaler is used as long as the left-hand side of equation (2) is greater than the right side. Under these circumstances, rather than solving for the standard Marshallian demand of inhaler use, q^*(o, f, s, z, l, y, r, w; t), we can treat q^* as a binomial process, with the probability that the inhaler is either used or not based on the surrounding conditions.

In general, however, we do not observe individual "puffs" of the inhaler either. Inhaler usage is only observed when the individual exhausts the metered doses and fills a new prescription. This can also be viewed as a binomial process with probability of a prescription being filled dictated by the surrounding conditions that determine inhaler use. If we aggregate the number of prescriptions filled over both space (e.g., zip code) and time (e.g., a quarter) then the number of potential prescriptions we might witness (i.e., the number of Bernoulli trials) grows large. Under these conditions, we can approximate the number of prescriptions filled as a Poisson process with the number of individuals in the area as the exposure variable. Because spatial variation in the exposure to pollution can lead to random variation in the probability of filling the prescriptions, a negative binomial model is appropriate to account for possible overdispersion. This leads to a model in which the expected number of prescriptions for the i^{th} zip code is

$$\#\, of\ Prescriptions_i = Pop_i \cdot e^{\beta X_i + \varepsilon} \qquad (3)$$

where Pop_i is the population for that zipcode and X_i is the vector of independent variables. ε is a mean zero error term capturing the unobserved heterogeneity. exp(ε) is assumed to have a gamma distribution with mean 1 and variance α, where α is the estimated parameter for overdispersion.

Methodology

The total count of prescriptions for quick relief asthma medication is explained using measures of asthma triggers and other cofactors. The study utilizes a dataset of asthma drug prescriptions for a large percentage of the pharmacies in the state of California and GIS layers of spatial factors.

In this study, our "health" outcome (filling asthma prescriptions) is not a "direct" effect of air pollution exposure, but rather a secondary effect. That is, the true sequence of events goes as follows: long-term exposure to air pollution makes an individual more susceptible to asthma triggers leading to an exacerbation of asthma symptoms which in turn causes an increase in asthma medication use. The increase in asthma medication use eventually (perhaps with a lag) leads to the filling of a prescription. Because the urgency with which a prescription will need to be filled will vary across individuals and with their initial stock of asthma medication, short-term effects will be difficult to observe. We, therefore, focus on longer periods of time during which increased air pollution should be correlated with increased prescriptions, over and above the amount necessary for normal stock replacement.

Prescription data are provided for each five-digit zip code in the state and are stratified by age and the level of asthma severity of the patient. We classified asthma severity using each patient's prescription history according to NIH Guidelines (1997). Asthma is thus classified as mild intermittent, mild persistent, moderate persistent, and severe, based upon the number and combination of prescriptions that the patient fills for both quick-relief and maintenance asthma medications over the 12 month calendar year. Generally, asthma medications fall into one of two categories: (1) short-term treatments intended to provide quick relief in the event of an asthma attack and (2) long-term maintenance therapies intended to prevent asthma attacks. Mild asthmatics are those patients prescribed a quick-relief medication only. Patients with mild persistent asthma not only are prescribed a quick-relief medication but also a single controller or maintenance therapy. Moderate asthmatics are prescribed two controllers operating by different modes of action in addition to the quick relief medications, while severe asthmatics are prescribed three controllers with different modes of action. Should an individual's asthma severity level shift over the 12 month period, the individual is assigned to the most severe of the categories for which he/she qualifies. Table 1 provides a list of the quick-acting asthma medications and the maintenance therapies.

Asthma triggers included in the study include air pollutants (e.g., particulate matter and ozone), which are the primary factors of concern, as well as temperature. Additional cofactors included are population demographics (e.g., median household income, percent urban population, race/ethnicity), and seasonal or quarterly dummies.

Data Description

The number of prescriptions for quick acting asthma medication was obtained from NDChealth (hereafter, NDC), a Phoenix-based company that maintains prescription-related data for marketing research. NDC maintains two related datasets, a "retail pharmacy" database and a "patient" database. The pharmacy database contains dispensing records from approximately 36,000 pharmacies nationwide, and captures approximately 70% of the volume of traditional pharmacy-dispensed prescriptions. Hospital, military and mail order pharmacies and prescriptions dispensed to institutionalized patients are not included.[3] The patient database is a subset of approximately 14,000 of the pharmacies in the retail pharmacy database. The patient database is a more "complete" database in that it includes the patient's age and gender, along with a unique patient identifier so that the history of a patient may be followed. Not included in the database, and unknown to NDC, is any information that could personally identify a patient (such as a name, address or phone number) and NDC has been careful not to release any individual patient data, even with an anonymous identifier.

[3] While these excluded prescriptions were a small component of the overall market for our period of study,

For this study, we use data extracted from the patient database to obtain the total counts of the number of prescriptions for quick-acting asthma medication in a five digit zip code for each quarter from 1998 to 2001. Data are given by quarter dispensed and the zip code of the dispensing pharmacy. These data are further disaggregated by the asthma severity experienced by the patient as well as their age group, defined as follows: ages 0 to 4, ages 5 to 9, ages 10-14, ages 15-17, ages 18-44, ages 45-64, ages 65 and up, and age unknown.

The prescription data used in this analysis are limited in the following way. They only include counts of prescriptions for quick relief asthma medication from those pharmacies that "consistently" report this information. "Consistent" reporting is defined by NDC as pharmacies for which fewer than 11 days of data are missing in any 30-day period. While the number of consistently reporting pharmacies remains relatively stable in a zip code over time, the number of pharmacies reporting across zip codes varies widely and may affect the number of prescriptions dispensed for quick relief asthma prescriptions.

The air pollution data come from the California Air Resource Board. Daily observations on the levels of various pollutants are available for almost 700 monitors covering all 58 counties in California, although each particular monitor only measures a subset of pollutants. PM10 (in micrograms per cubic meter) and the 8-hour maximum value of ozone (in parts per million) were available for 54 of the counties. The daily observations for all of the pollution measures were averaged over the quarter for each

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mail-order pharmacy sales were the fastest growing sector of the U.S. prescription drug retail market in monitor.

The weather data come from the National Climatic Data Center. Daily observations for weather data such as the average, minimum, and maximum temperature, precipitation, and dew point temperature, as well as the minimum and maximum relative humidity, are reported for 43 active weather stations in 20 counties in California. The average, minimum, and maximum temperature values were available for all of these stations. The dew point temperature was also considered as an explanatory variable, but was only available for 25 monitors in 14 counties. Since it is generally believed that cold, dry air may also trigger asthma attacks (Kaminsky et al. 2000), the average minimum temperature over the quarter was included in this analysis.

While the coverage of air pollution and weather data offer an acceptable representation of the state, each zip code does not necessarily contain an air pollution or weather monitor. We use a combination of geostatistical data methods (Kaluzny et al. 1998, Schabenberger and Gotway 2005) to link two disparate points: the zip code and the air pollution monitor or the weather station. We first used a locally weighted polynomial regression to predict the quarterly value of ozone, PM10, and minimum temperature. This was done by running a LOESS regression of the quarterly pollution or temperature values for all of the monitoring station as a function of the station's latitude, longitude, and elevation, and then using the results to predict the value for each zip code in California. While this step captured the geographic trends in these variables, we then corrected for

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2004 (Health Strategies Consultancy 2005) so the approach used here may be problematic in the future.

any remaining small scale random variation in the error term through the use of ordinary kriging. This was done by modeling the detrended residuals from the LOESS regression for each monitoring station as an exponential, spatially autocorrelated function and then predicting the residual for each zip code. The sum of the LOESS regression and the kriging results provides a spatially-appropriate prediction of the ambient pollution and weather conditions for each zip code.

Demographic data for each zip code were obtained from the 2000 U.S. Census. Total population counts by age and race, as well as other demographic data, were collected at the zip code level from both the SF1 (100-percent, short form) and SF3 (sample, long form) datasets. Population is used as the exposure variable in the negative binomial models. We control for other characteristics of the population (the percent of the population in each race, percent of the zip code classified as urban, and the median income) explicitly on the left-hand side of the equation.

The summary statistics for the data used in this analysis are listed in Table 2. The unit of observation is the five-digit zip code. For the sixteen quarters from 1998 to 2001, data were available for 852 of the 1919 zip codes in California. Together, over 13,000 observations of quarterly counts for quick relief medications were available. When linked with the regressors, however, available observations ranged between 10,467 and 11,232.

Results

Since our prescription data were reported as counts for each five-digit zip code, we control for the variation in population across zip codes by using the total population of the zip code from the 2000 Census as the exposure variable in our negative binomial model. The pollution variables of interest, PM_{10} and ozone, are included as both linear and quadratic terms. The effects of cold temperature extremes are captured using the average minimum temperature for the zip code over the quarter and cyclical variation and seasonal allergies are controlled for using quarterly dummies. Demographic variables include the percent of the zip code classified by race and ethnicity (i.e., the percent black, percent Asian, and percent Latino), the percent of the zip code classified as urban, median household income, and an interaction between percent urban and median income. Finally, we have included a trend variable to control for annual changes that are not otherwise captured. Results for the negative binomial model are reported in Tables 3 through Table 8.

The second column of Table 3 reports the results for the count of *all* prescriptions regressed on our explanatory variables and is our most aggregated model. Focusing first on the demographic variables, household income is negative and statistically significant, suggesting that households with lower incomes fill more asthma prescriptions. Surprisingly, percent urban is also negative, suggesting that individuals living in urban areas are less likely to fill asthma prescriptions. We had expected that urbanization would be correlated with asthma triggers more common in urban environments (e.g., dust mites, mold, and cockroach waste) but this is not evident in these results. However, neither household income nor percent urban can be evaluated in isolation because of the interaction term. A better way of evaluating the aggregate effect is to look at the elasticity of the variable including the interaction term. From equation (3), the elasticity of the expected number of prescriptions for any variable *i* is βX_i, which is the estimated coefficient times the mean value of the independent variable. Including the interaction term implies an elasticity of -0.332 for median household income, so a 10% increase in median income (about $5,100) across the state of California would decrease the average number of total prescriptions for inhalers by about 3.32% (about 23 prescriptions) for each zip code each quarter. The elasticity for percent urban is -0.723, implying that a 1% increase in average urbanization would decrease the number of inhaler prescriptions across the state by about 6 prescriptions per zip code per quarter.

Race dummies were significant in this regression, although we had no prior as to the direction of the coefficient, recognizing only that race could be a significant determinant of exposure to triggers and/or susceptibility to them. We find that percent Latino has a positive effect on prescription purchases for quick relief medication while percent Asian and percent Black has a negative effect on asthma prescriptions for quick relief medications.

The coefficients on a few other non-pollution variables are also worth noting. The coefficient on minimum temperature is negative and significant, capturing the effect of cold weather as an asthma trigger. As the average minimum temperature declines across our sample, the number of asthma inhaler prescriptions increases. In addition, the dummy variable for summer is negative and significant, suggesting that after having controlled for ambient pollution levels directly, we observe statistically fewer inhaler prescriptions in the summer months. Finally, the time trend variable is positive and significant, reflecting the fact that asthma diagnosis and treatment has been rising over time (Moorman et al. 2007).

Turning to our pollution variables of interest, we find mixed results. The coefficient on the linear term for ozone is negative and significant, which is a perverse result. In later models, we find that this is a more nuanced effect. Contributing to this result could be the way in which ozone enters into our model. We use the maximum 8-hour measurement of ozone which may not capture acute effects on asthma exacerbation as well as the one-hour measures. We were unable to use the one-hour measures due to incomplete data.

On the other hand, PM_{10} has a positive and statistically significant effect on asthma prescriptions for quick relief medications. This means that higher levels of PM_{10} are associated with a greater number of total prescriptions for quick relief asthma medications. The squared term on PM_{10} is also significant, implying a non-linear relationship. The elasticity of PM_{10} at mean values is $\beta_1 * PM10 + 2 * \beta_2 * PM10^2 = 0.242$, implying a 10% increase in PM_{10} increases total prescriptions for inhalers by 2.5%.

However, since we've included a quadratic relationship for PM_{10} (that is, we have both a linear term β_1 and a squared term, β_2 in our regression), the turning point for this relationship is of interest. Taking the first derivative of our modeled equation (3) with respect to PM_{10} and setting it equal to zero, we can solve for the turning point, which is when $PM_{10} = \beta 1/(2 * \beta 2)$. Using the coefficients from our regression, we estimate that the turning point occurs just after 65 $\mu g/m^3$. The summary statistics in Table 2 indicate that this is more than 2½ standard deviations above our mean value, but still within the range of our quarterly PM_{10} estimates. In other words, the effect of PM_{10} on prescriptions appears to be greater at lower levels of PM_{10} and levels off around 65 $\mu g/m^3$. Exposure modification could occur on high pollution days with asthmatics choosing to stay indoors to avoid exposure and exacerbation of their condition.

Effects by Asthma Severity

Recognizing that maintenance therapies could be dampening the effects of air pollution on quick-relief asthma medication use and prescriptions, we stratified our data according to asthma severity. Using counts of prescriptions per capita for each severity level as the dependent variable, we ran four separate regressions: one for prescriptions for quick relief medication for mild intermittent asthmatics (patients who use no other controlling medication), another for mild persistent asthmatics (those using one controlling medication), a third for moderate asthmatics (those using two controlling medications), and a fourth for severe asthmatics (those using three or more controlling medications). These results are reported in Table 3. With the exception of the effects of the pollution variables and quarterly dummies, the sign and significance of our coefficients remain largely unchanged from the total prescription model.

As was the case when we used all prescriptions, PM_{10} has a consistently positive and statistically significant effect on asthma prescriptions for quick relief medications regardless of severity level. However, we see a difference in the magnitude of the response to PM_{10} levels based on asthma severity, with mild intermittent asthmatics showing the largest response. This is not entirely surprising since mild intermittent asthmatics by definition do not take controller medications but rely only on the quick relief medications to ease their breathing. As a result, they might be more susceptible to asthma exacerbation as particulate pollution increases. Evaluating our model using the mean values for our variables reported in Table 2 and finding the elasticity as we did above, we find that PM_{10} has an elasticity of 0.272 for mild intermittent asthmatics, implying that a 10% increase in PM_{10} increases total prescriptions for inhalers by 2.7%. In contrast, mild persistent asthmatics show the smallest response, with elasticity of 0.189.

The effect of ozone levels on asthma prescriptions remains a puzzle. Except for severe asthmatics, the linear term for ozone is negative, and is significant for mild intermittent and mild persistent asthmatics. One possibility is that we are not adequately capturing the seasonal effects of ozone in our model. Future work will explore alternative specifications that may include interaction variables.

Age-Specific Effects

Given the dramatic rise in asthma among children (Moorman, et al. 2007), it is important to determine whether or not the effects described above are age-specific. Including age-specific cofactors (such as the percentage of specific age groups in each zip code) in the models above was considered, but using the prescriptions by age group in separate regressions gives a much more complete picture.

The results for our negative binomial model run by specific age group (i.e., ages 0-4, 5-9, 10-14, 15-17, and 18 and older) are reported in Tables 4 through 8. Note that these regressions use only observations for which age is known. In contrast, Table 3 reports results for all ages combined, including those of "unknown" age.

In general, the models yield relationships for the non-pollution related variables of the same form as found in Table 3. One exception is that the effect of percent urban and household income becomes insignificant in the models for severe asthmatics in the age groups 0-4, and 15-17. Another exception is that, whereas the dummy variable for percent black is negative and significant in the regression for combined ages in Table 3, the coefficient is *positive* and generally significant for the three youngest age groups and generally negative and significant in the older age categories. This suggests that air pollution-induced asthma exacerbation among the black population may vary by age.

Turning to our first pollution variable of interest, the linear term for PM_{10} is always positive and significant across age groups and severity levels for the three youngest age categories (0-4, 5-9, and 10-14), indicating that prescriptions increase with PM_{10} levels, as expected.

The effect of PM_{10} on prescriptions for ages 15-17 (Table 7) requires more discussion. For total prescriptions and severe persistent asthmatics in this age group, the liner term on PM_{10} is insignificant, but the squared term is positive and significant, suggesting that asthma exacerbation increases with PM_{10} at an increasing rate. For the mild persistent model, the linear PM_{10} term is *negative* and significant and the squared term is positive and significant. At first, this may appear to be a perverse result, but the turning point is at about 25 $\mu g/m^3$, below the mean PM_{10} value for this sample. This suggests that after this turning point is reached, prescriptions increase at an increasing rate with PM10 levels. These results taken in total suggest that the prophylactic use of preventive medication mitigates asthmatic responses at lower levels of PM_{10} for this group, but increases beyond some “threshold” exhaust the ability of the preventive medication to mitigate exacerbations.

It should also be noted that the top three severity classes for children (with the exception of severe asthmatics aged 0-4 and moderate asthmatics aged 15-17) all show an unambiguous increasing relationship (beyond any turning point) between the number of prescriptions and PM_{10}. The only severity level that displays a leveling off effect for PM_{10} is the one for mild intermittent asthmatics. The effect of PM_{10} on prescriptions for adults is only significant for mild intermittent asthmatics, where there is also a leveling off effect.

As mentioned above, the impact of ozone across ages and severity level is more nuanced than the impact of PM_{10}. The linear term for ozone is both positive and generally significant for ages 5 through 17 (that is, Tables 5, 6, and 7). It is also significant for the severe model in Table 4 (ages 0-4). For these models, prescriptions appear to increase with ozone. The exception is the negative and significant squared term for the quick relief model in Table 5. In contrast, a number of models in Tables 4 and 8 (age groups 0-4 and all other ages) have a negative and significant linear term for ozone. This is odd in that is suggests a negative relationship between prescriptions for quick relief inhalers and ozone for these groups. Calculating the turning point when the squared term is positive and significant, suggests that a turning point between 0.06 and 0.075 ppm, well beyond the mean ozone level in the sample. One possible explanation for this perverse result is that adults and very young children for whom decisions are almost totally dictated by adults are more likely to stay indoors during high ozone days, which are announced on the radio and television. The mixed results for ozone when disaggregated by age also help explain the negative and significant coefficient for ozone in the models for all ages combined. It appears that results for the adult group is the dominating effect in the model for all ages, which is not surprising given the larger number of prescriptions filled for this group. As mention above, there may also be an effect of using an 8-hour average versus 1-hour average for ozone.

Conclusion

With the growing concern about increasing asthma rates, studies that further our understanding of the causes of asthma exacerbation are timely. If, as our study shows, chronic exposure to higher levels of air pollution leads to increases in asthma symptoms and the use of asthma medication, then reductions in these air pollutants will produce benefits that have previously been difficult to quantify. The benefits of reducing *serious* asthma attacks can be analyzed by examining emergency room visits and hospital admissions. The benefits associated with a decline in the outcomes analyzed here, the reduced use of quick acting asthma medication, associated with longer term exposures have been somewhat more elusive as they are not as easily observable as ER visits. In contrast to diary studies, which examine the effect of short-term exposure to air pollution, this study looks at the effect of longer term or chronic exposures to air pollution on asthma symptoms by examining prescription data at the zip code level for California.

The results of Table 3 show a statistically significant positive association between total prescriptions for quick-acting asthma medication and air pollution. Including measures for both ozone and PM_{10}, and controlling for temperature and demographics, we find that PM_{10} is an important driver in explaining the increase in prescriptions, but ozone has a perverse effect when all ages and severity levels are modeled together. This is also true when we disaggregate our model by severity class but keep our ages combined.

When we disaggregate our models of prescription counts by age classes and severity, presented in Tables 4 through 8, however, the results are more nuanced.

Disaggregation by age class suggests that prescriptions for quick-acting inhalers for children increases with PM_{10}, and this relationship generally does not show a leveling off effect except for mild intermittent asthmatics. Ozone also generally increases the number of prescriptions for ages 5-17, as well as for severe asthmatics and some moderate asthmatics at younger ages. However, prescriptions and ozone show the opposite relationship for the adults and the very young (ages 0-4).

As a general conclusion, though, we find that there appears to be a positive relationship between asthma and both PM_{10} and ozone levels. This suggests that there are real consequences to long term exposure to air pollution, one which has previously not been modeled in this way. These results shed some light on the benefits of reduced air pollution exposure to asthmatics.

<u>Table 1: Asthma Prescriptions Medications</u>

<u>Symptomatic Therapy (Quick Relief)</u>
Albuterol
Bitolterol
Isoetharine
Metaproteronol
Pirbuterol
Terbutaline

<u>Controller Therapy (Long term preventative)</u>
Inhaled Corticosteroids
  Beclomethasone
  Budesonide
  Flunisolide
  Fluticasone
  Triamcinolone
Leukotriene Antagonists
  Motelukast
  Zafirlukast
  Zileutin
Long Acting Beta Agonists
  Salmeterol
Xanthine Derivatives
  Aminophylline
  Dyphylline
  Oxtriphylline
  Theophylline
Mast Cell Stabilizers
  Cromolym
  Nedocromil

Table 2: Summary Statistics

Age Group	*Asthma Severity*	*Number of Observations*[a]	*Mean*	*Standard Deviation*	*Median*	*Minimum*	*Maximum*
All Ages[b]	Total Prescriptions	10,787	703.60	481.59	585	19	3,477
	Mild Intermittent		337.62	238.33	276	9	1,819
	Mild Persistent		210.00	144.96	174	4	975
	Moderate		104.67	72.97	88	0	516
	Severe		51.31	40.11	42	0	297
Age 0-4	Total Prescriptions	11,392	30.41	31.45	21	1	416
	Mild Intermittent		18.78	20.51	13	0	300
	Mild Persistent		8.60	9.89	6	0	153
	Moderate		2.44	3.63	1	0	46
	Severe		0.59	1.55	0	0	26
Age 5-9	Total Prescriptions	11,574	45.80	42.28	34	1	354
	Mild Intermittent		24.96	23.67	18	0	217
	Mild Persistent		13.76	13.90	10	0	146
	Moderate		5.16	6.03	3	0	51
	Severe		1.92	3.34	0	0	42
Age 10-14	Total Prescriptions	11,621	55.23	48.06	42	1	391
	Mild Intermittent		29.74	25.88	23	0	192
	Mild Persistent		15.70	14.97	12	0	146
	Moderate		6.70	7.43	4	0	66
	Severe		3.10	4.48	1	0	47
Age 15-17	Total Prescriptions	11,400	26.11	22.64	20	1	181
	Mild Intermittent		15.17	13.32	11	0	105
	Mild Persistent		6.95	7.02	5	0	74
	Moderate		2.77	3.67	1	0	37
	Severe		1.22	2.38	0	0	24
Adults[c]	Total Prescriptions	10,787	612.64	429.43	505	15	3,031
	Mild Intermittent		303.41	217.23	247	9	1,605
	Mild Persistent		179.12	126.40	147	3	897
	Moderate		87.43	65.21	71	0	499
	Severe		42.69	36.43	33	0	273

[a] Observations are counts of prescriptions for each calendar quarter in a five-digit zip code.
[b] Prescription counts for the "All Ages" category *includes* prescriptions for individuals where the age is unknown.
[c] Prescription counts for the "Adults" category *does not include* prescriptions for individuals where the age is unknown.

Table 2: Summary Statistics (continued)

Variable	*Number of Observations*	*Mean*	*Standard Deviation*	*Median*	*Minimum*	*Maximum*
Population	13,013	34,391.63	18,967.45	31,866	214	105,275
PM 10	12,811	33.48	12.01	33.32	0.35	94.15
PM 10 Squared	12,811	1,265.17	880.59	1,110.43	0.12	8,864.77
Ozone 8 Hour Max	12,656	0.04	0.01	0.04	0.01	0.10
Ozone 8 Hour Max Squared	12,656	0.00	0.00	0.00	0.00	0.01
Minimum Temperature	12,647	52.17	8.92	51.88	2.03	81.22
Percent Urban	13,013	92.8%	18.5%	100.0%	0.0%	100.0%
Median Household Income	13,013	51,186.39	20,559.34	46,806	8,855	164,479
Urban % * Med. HH Income	13,013	47,988.77	22,011.64	45,043.18	0	141,527
Percent Black	13,013	5.7%	9.0%	2.5%	0.0%	78.5%
Percent Asian	13,013	10.2%	11.0%	6.3%	0.1%	59.0%
Percent Latino	13,013	71.8%	21.9%	78.7%	2.8%	97.8%

Table 3: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, All Ages[b] Combined Exposure Variable = Population

All Ages[b]	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.017	0.00	***	0.022	0.00	***	0.010	0.00	***	0.016	0.00	***	0.014	0.00	***
PM 10 Squared	-1.34E-04	0.00	***	-1.84E-04	0.00	***	-6.23E-05	0.05	**	-1.11E-04	0.00	***	-9.58E-05	0.01	***
Ozone 8 Hour Max	-7.235	0.02	**	-6.072	0.05	**	-10.328	0.00	***	-3.821	0.24		1.129	0.76	
Ozone 8 Hour Max Squared	40.187	0.19		23.620	0.44		69.616	0.03	**	15.452	0.64		-8.056	0.83	
Minimum Temperature	-0.004	0.00	***	-0.002	0.05	*	-0.005	0.00	***	-0.005	0.00	***	-0.004	0.00	***
Percent Urban	-3.753	0.00	***	-3.649	0.00	***	-3.850	0.00	***	-3.862	0.00	***	-3.162	0.00	***
Median Household Income	-6.04E-05	0.00	***	-5.79E-05	0.00	***	-6.39E-05	0.00	***	-6.47E-05	0.00	***	-5.10E-05	0.00	***
Urban % * Med. HH Income	5.81E-05	0.00	***	5.57E-05	0.00	***	6.18E-05	0.00	***	6.25E-05	0.00	***	4.69E-05	0.00	***
Percent Black	-0.790	0.00	***	-0.820	0.00	***	-0.609	0.00	***	-0.970	0.00	***	-0.884	0.00	***
Percent Asian	-1.098	0.00	***	-1.092	0.00	***	-1.008	0.00	***	-1.210	0.00	***	-1.196	0.00	***
Percent Latino	1.219	0.00	***	1.136	0.00	***	1.153	0.00	***	1.446	0.00	***	1.633	0.00	***
April-June (Spring) Dummy	0.016	0.54		-0.066	0.01	**	0.110	0.00	***	0.069	0.01	**	-0.005	0.88	
July-Sept (Summer) Dummy	-0.086	0.01	***	-0.222	0.00	***	0.052	0.09	*	0.022	0.49		-0.071	0.05	*
Oct-Dec (Fall) Dummy	-0.041	0.03	**	-0.070	0.00	***	0.037	0.05	**	-0.063	0.00	***	-0.138	0.00	***
Time Trend	0.003	0.07	*	0.005	0.00	***	-0.006	0.00	***	0.008	0.00	***	0.020	0.00	***
Constant	-0.716	0.00	***	-1.660	0.00	***	-1.508	0.00	***	-2.726	0.00	***	-4.402	0.00	***
Alpha	0.387			0.388			0.397			0.422			0.529		
Number of Observations	10,467			10,467			10,467			10,467			10,467		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

[b] Prescription counts for the "All Ages" category *includes* prescriptions for individuals where the age is unknown.

Table 4: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, Age 0-4
Exposure Variable = Population

Age 0-4	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.019	0.00	***	0.023	0.00	***	0.006	0.07	*	0.012	0.03	**	0.018	0.09	*
PM 10 Squared	-1.02E-04	0.01	**	-1.44E-04	0.00	***	5.19E-05	0.26		-3.81E-05	0.58		-2.63E-04	0.06	*
Ozone 8 Hour Max	-9.875	0.02	**	-10.370	0.01	**	-1.954	0.68		-7.527	0.29		24.986	0.08	*
Ozone 8 Hour Max Squared	35.685	0.38		7.050	0.87		37.726	0.43		46.185	0.52		-206.132	0.15	
Minimum Temperature	-0.005	0.00	***	-0.003	0.05	**	-0.008	0.00	***	-0.006	0.02	**	0.001	0.87	
Percent Urban	-3.564	0.00	***	-2.784	0.00	***	-4.206	0.00	***	-2.113	0.00	***	0.382	0.61	
Median Household Income	-5.49E-05	0.00	***	-4.10E-05	0.00	***	-7.38E-05	0.00	***	-3.88E-05	0.00	***	1.04E-05	0.51	
Urban % * Med. HH Income	5.87E-05	0.00	***	4.37E-05	0.00	***	7.81E-05	0.00	***	4.53E-05	0.00	***	-1.39E-06	0.93	
Percent Black	1.174	0.00	***	1.213	0.00	***	1.321	0.00	***	0.565	0.00	***	0.128	0.69	
Percent Asian	-0.368	0.00	***	-0.289	0.00	***	-0.394	0.00	***	-0.654	0.00	***	-0.911	0.00	***
Percent Latino	0.194	0.00	***	0.117	0.02	**	0.257	0.00	***	0.778	0.00	***	0.488	0.01	***
April-June (Spring) Dummy	-0.239	0.00	***	-0.292	0.00	***	-0.226	0.00	***	-0.144	0.02	**	-0.490	0.00	***
July-Sept (Summer) Dummy	-0.473	0.00	***	-0.545	0.00	***	-0.435	0.00	***	-0.335	0.00	***	-0.695	0.00	***
Oct-Dec (Fall) Dummy	-0.213	0.00	***	-0.259	0.00	***	-0.090	0.00	***	-0.266	0.00	***	-0.541	0.00	***
Time Trend	0.038	0.00	***	0.030	0.00	***	0.042	0.00	***	0.087	0.00	***	0.172	0.00	***
Constant	-3.913	0.00	***	-5.063	0.00	***	-4.599	0.00	***	-8.729	0.00	***	-14.280	0.00	***
Alpha	0.633			0.632			0.790			1.502			5.166		
Number of Observations	11,025			11,025			11,025			11,025			11,025		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

Table 5: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, Age 5-9
Exposure Variable = Population

Age 5-9	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.021	0.00	***	0.029	0.00	***	0.007	0.03	**	0.012	0.00	***	0.017	0.01	**
PM 10 Squared	-1.36E-04	0.00	***	-2.30E-04	0.00	***	3.65E-05	0.39		-4.91E-05	0.36		-1.29E-04	0.14	
Ozone 8 Hour Max	3.330	0.39		4.872	0.22		1.975	0.65		15.219	0.01	***	21.371	0.01	**
Ozone 8 Hour Max Squared	-40.344	0.29		-75.899	0.05	*	-7.368	0.86		-92.204	0.09	*	-131.269	0.12	
Minimum Temperature	-0.004	0.00	***	-0.002	0.19		-0.006	0.00	***	-0.005	0.02	**	-0.016	0.00	***
Percent Urban	-4.174	0.00	***	-3.846	0.00	***	-3.627	0.00	***	-3.361	0.00	***	-3.647	0.00	***
Median Household Income	-6.23E-05	0.00	***	-5.35E-05	0.00	***	-5.97E-05	0.00	***	-5.34E-05	0.00	***	-7.87E-05	0.00	***
Urban % * Med. HH Income	6.75E-05	0.00	***	5.89E-05	0.00	***	6.38E-05	0.00	***	5.97E-05	0.00	***	8.17E-05	0.00	***
Percent Black	0.969	0.00	***	0.879	0.00	***	1.208	0.00	***	0.796	0.00	***	0.830	0.00	***
Percent Asian	-0.578	0.00	***	-0.561	0.00	***	-0.566	0.00	***	-0.535	0.00	***	-0.676	0.00	***
Percent Latino	0.194	0.00	***	0.157	0.00	***	0.087	0.10	*	0.448	0.00	***	1.029	0.00	***
April-June (Spring) Dummy	-0.096	0.00	***	-0.123	0.00	***	-0.075	0.04	**	-0.211	0.00	***	-0.214	0.00	***
July-Sept (Summer) Dummy	-0.228	0.00	***	-0.288	0.00	***	-0.175	0.00	***	-0.331	0.00	***	-0.312	0.00	***
Oct-Dec (Fall) Dummy	0.047	0.04	**	0.057	0.01	**	0.090	0.00	***	-0.068	0.03	**	-0.238	0.00	***
Time Trend	0.026	0.00	***	0.020	0.00	***	0.023	0.00	***	0.055	0.00	***	0.093	0.00	***
Constant	-3.415	0.00	***	-4.534	0.00	***	-4.733	0.00	***	-7.020	0.00	***	-7.897	0.00	***
Alpha	0.598			0.594			0.674			0.975			2.242		
Number of Observations	11,190			11,190			11,190			11,190			11,190		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

Table 6: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, Age 10-14
Exposure Variable = Population

Age 10-14	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.016	0.00	***	0.021	0.00	***	0.007	0.05	**	0.009	0.04	**	0.010	0.05	*
PM 10 Squared	-8.21E-05	0.04	**	-1.47E-04	0.00	***	3.29E-05	0.45		2.60E-05	0.63		-4.38E-05	0.52	
Ozone 8 Hour Max	12.854	0.00	***	11.807	0.00	***	13.474	0.00	***	21.295	0.00	***	22.008	0.00	***
Ozone 8 Hour Max Squared	-83.704	0.03	**	-81.647	0.03	**	-91.496	0.03	**	-114.174	0.03	**	-110.421	0.12	
Minimum Temperature	-0.009	0.00	***	-0.008	0.00	***	-0.007	0.00	***	-0.009	0.00	***	-0.018	0.00	***
Percent Urban	-3.810	0.00	***	-3.695	0.00	***	-3.692	0.00	***	-2.740	0.00	***	-0.283	0.42	
Median Household Income	-5.29E-05	0.00	***	-5.21E-05	0.00	***	-5.23E-05	0.00	***	-3.63E-05	0.00	***	5.35E-06	0.48	
Urban % * Med. HH Income	5.76E-05	0.00	***	5.71E-05	0.00	***	5.70E-05	0.00	***	3.96E-05	0.00	***	-3.28E-06	0.68	
Percent Black	0.398	0.00	***	0.326	0.00	***	0.675	0.00	***	0.268	0.05	**	0.214	0.25	
Percent Asian	-0.933	0.00	***	-0.845	0.00	***	-0.852	0.00	***	-1.138	0.00	***	-1.539	0.00	***
Percent Latino	0.402	0.00	***	0.438	0.00	***	0.201	0.00	***	0.677	0.00	***	0.681	0.00	***
April-June (Spring) Dummy	-0.079	0.02	**	-0.096	0.00	***	-0.046	0.21		-0.188	0.00	***	-0.196	0.00	***
July-Sept (Summer) Dummy	-0.156	0.00	***	-0.176	0.00	***	-0.133	0.00	***	-0.273	0.00	***	-0.225	0.00	***
Oct-Dec (Fall) Dummy	0.005	0.84		0.030	0.18		0.046	0.07	*	-0.123	0.00	***	-0.248	0.00	***
Time Trend	0.029	0.00	***	0.022	0.00	***	0.025	0.00	***	0.057	0.00	***	0.086	0.00	***
Constant	-3.657	0.00	***	-4.480	0.00	***	-4.801	0.00	***	-7.237	0.00	***	-10.165	0.00	***
Alpha	0.590			0.564			0.686			0.966			1.736		
Number of Observations	11,232			11,232			11,232			11,232			11,232		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

Table 7: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, Age 15-17
Exposure Variable = Population

Age 15-17	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.001	0.76		0.005	0.12		-0.010	0.00	***	0.002	0.72		-0.007	0.37	
PM 10 Squared	8.08E-05	0.04	**	3.02E-05	0.45		2.10E-04	0.00	***	6.24E-05	0.34		1.99E-04	0.04	**
Ozone 8 Hour Max	10.015	0.01	***	12.381	0.00	***	8.927	0.06	*	18.671	0.01	***	14.474	0.14	
Ozone 8 Hour Max Squared	-41.480	0.28		-68.961	0.08	*	-20.077	0.67		-98.209	0.14		-12.804	0.90	
Minimum Temperature	-0.011	0.00	***	-0.009	0.00	***	-0.011	0.00	***	-0.010	0.00	***	-0.022	0.00	***
Percent Urban	-3.750	0.00	***	-3.408	0.00	***	-2.679	0.00	***	-4.606	0.00	***	-2.424	0.00	***
Median Household Income	-5.52E-05	0.00	***	-5.07E-05	0.00	***	-3.39E-05	0.00	***	-7.80E-05	0.00	***	-4.01E-05	0.00	***
Urban % * Med. HH Income	5.75E-05	0.00	***	5.35E-05	0.00	***	3.44E-05	0.00	***	8.08E-05	0.00	***	4.23E-05	0.00	***
Percent Black	-0.235	0.02	**	-0.293	0.00	***	-0.103	0.39		-0.464	0.01	***	0.533	0.04	**
Percent Asian	-1.018	0.00	***	-0.970	0.00	***	-0.800	0.00	***	-1.472	0.00	***	-1.569	0.00	***
Percent Latino	0.647	0.00	***	0.639	0.00	***	0.520	0.00	***	0.852	0.00	***	1.139	0.00	***
April-June (Spring) Dummy	-0.101	0.00	***	-0.156	0.00	***	-0.062	0.12		-0.142	0.01	**	-0.101	0.24	
July-Sept (Summer) Dummy	-0.171	0.00	***	-0.235	0.00	***	-0.141	0.00	***	-0.186	0.01	***	-0.148	0.13	
Oct-Dec (Fall) Dummy	-0.015	0.52		-0.003	0.90		0.002	0.95		-0.066	0.10	*	-0.183	0.00	***
Time Trend	0.023	0.00	***	0.017	0.00	***	0.027	0.00	***	0.042	0.00	***	0.065	0.00	***
Constant	-3.950	0.00	***	-4.980	0.00	***	-6.001	0.00	***	-5.892	0.00	***	-8.586	0.00	***
Alpha	0.566			0.551			0.745			1.434			3.316		
Number of Observations	11,011			11,011			11,011			11,011			11,011		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level

Table 8: Negative Binomial Regressions of Prescriptions Counts by Asthma Severity, Adults[c]
Exposure Variable = Population

Adults[c]	Total Prescriptions			Mild Intermittent			Mild Persistent			Moderate			Severe		
	Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value		Coefficient	p-value	
PM 10	0.011	0.00	***	0.018	0.00	***	0.002	0.39		0.004	0.16		-0.001	0.80	
PM 10 Squared	-6.60E-05	0.04	**	-1.42E-04	0.00	***	1.98E-05	0.54		1.06E-05	0.76		3.51E-05	0.37	
Ozone 8 Hour Max	-9.765	0.00	***	-7.407	0.02	**	-13.035	0.00	***	-8.666	0.01	**	-4.662	0.24	
Ozone 8 Hour Max Squared	67.742	0.03	**	40.193	0.19		99.204	0.00	***	68.929	0.04	**	50.191	0.20	
Minimum Temperature	-0.005	0.00	***	-0.003	0.00	***	-0.006	0.00	***	-0.007	0.00	***	-0.005	0.00	***
Percent Urban	-3.482	0.00	***	-3.466	0.00	***	-3.504	0.00	***	-3.398	0.00	***	-2.516	0.00	***
Median Household Income	-5.58E-05	0.00	***	-5.45E-05	0.00	***	-5.78E-05	0.00	***	-5.75E-05	0.00	***	-4.05E-05	0.00	***
Urban % * Med. HH Income	5.30E-05	0.00	***	5.21E-05	0.00	***	5.50E-05	0.00	***	5.44E-05	0.00	***	3.53E-05	0.00	***
Percent Black	-0.796	0.00	***	-0.810	0.00	***	-0.609	0.00	***	-1.030	0.00	***	-1.000	0.00	***
Percent Asian	-1.098	0.00	***	-1.092	0.00	***	-1.008	0.00	***	-1.215	0.00	***	-1.238	0.00	***
Percent Latino	1.229	0.00	***	1.148	0.00	***	1.167	0.00	***	1.487	0.00	***	1.645	0.00	***
April-June (Spring) Dummy	0.015	0.57		-0.048	0.08	*	0.097	0.00	***	0.040	0.17		-0.040	0.24	
July-Sept (Summer) Dummy	-0.097	0.00	***	-0.210	0.00	***	0.028	0.38		-0.016	0.62		-0.112	0.00	***
Oct-Dec (Fall) Dummy	-0.066	0.00	***	-0.063	0.00	***	-0.005	0.78		-0.148	0.00	***	-0.235	0.00	***
Time Trend	0.027	0.00	***	0.019	0.00	***	0.022	0.00	***	0.047	0.00	***	0.066	0.00	***
Constant	-1.061	0.00	***	-1.928	0.00	***	-1.935	0.00	***	-3.219	0.00	***	-5.047	0.00	***
Alpha	0.393			0.394			0.409			0.453			0.596		
Number of Observations	10,467			10,467			10,467			10,467			10,467		

*** indicates that the coefficient is significant at the 1% level, ** indicates significance at the 5% level, * indicates significance at the 10% level
[c] Prescription counts for the "Adults" category *does not include* prescriptions for individuals where the age is unknown

References

American Lung Association (2008). Childhood Asthma Overview. Available at: http://www.lungusa.org/site/c.dvLUK9O0E/b.22782/k.8D9C/Childhood_Asthma__Overview.htm. Accessed on January 22, 2008.

Delfino, Ralph J., Robert S. Zeiger, James M. Seltzer, Donald H. Street, and Christine E. McLaren (2002). Association of Asthma Symptoms with Peak Particulate Air Pollution and Effect Modification by Anti-Inflammatory Medication Use. *Environmental Health Perspectives* 110(10): A607-A617.

Gent, Janneane F., Elizabeth W. Triche, Theodore R. Holford, Kathleen Belanger, Michael B. Bracken, William S. Beckett, and Brian P. Leaderer (2003). Association of Low-Level Ozone and Fine Particles With Respiratory Symptoms in Children With Asthma. *Journal of the American Medical Association* 290(14): 1859-1867.

Hajat, S., A. Haines, S. A. Goubet, R.W. Atkinson and H.R. Anderson (1998). Association of Air Pollution with Daily GP Consultations for Asthma and Other Lower Respiratory Conditions in London. *Thorax*. 54: 597-605.

Health Strategies Consultancy (2005) *Follow The Pill: Understanding the U.S. Commercial Pharmaceutical Supply Chain*. Access on October 8, 2008 from http://www.kff.org/rxdrugs/7296.cfm

Hiltermann, T.J.N., J. Stolk, S.C. van der Zee, B. Brunekreef, C.R. de Bruijne, P.H. Fischer, C.B. Ameling, P.J. Sterk, P.S. Hiemstra, and L. van Bree (1998). Asthma Severity and Susceptibility to Air Pollution. *European Respiratory Journal*. 11: 686-693.

Jalaludin, Bin B., Brian I. O'Toole, and Stephen R. Leeder (2004). Acute effects of urban ambient air pollution on respiratory symptoms, asthma medication use, and doctor visits for asthma in a cohort of Australian children. Environmental Research 95: 32-42.

Kaluzny, Stephen P., Silvia C. Vega, Tamre P. Cardoso, and Alice A. Shelly (1998). *S+ Spatial Stats*. New York: Springer.

Kaminsky, David A., Jason H.T. Bates, and Charles G. Irvin (2000). Effects of Cool, Dry Air Stimulation on Peripheral Lung Mechanics in Asthma. *American Journal of Respiratory and Critical Care Medicine*. 162(1): 179-186.

Krupnick, Alan J., Winston Harrington, Bart Ostro (1990). Ambient Ozone and Acute Health Effects: Evidence from Daily Data. *Journal of Environmental Economics and Management*. 18:1-18.

Lewis, Toby C., Thomas G. Robins, J. Timothy Dvonch, Gerald J. Keeler, Fuyuen Y. Yip, Graciela B. Mentz, Xihong Lin, Edith A. Parker, Barbara A. Israel, Linda Gonzalez, and Yolanda Hill (2005). Air Pollution-Associated Changes in Lung Function among Asthmatic Children in Detroit. Environmental Health Perspectives 113(8): 1068-1075.

Moore, Kelly, Romain Neugebauer, Fred Lurmann, Jane Hall, Vic Brajer, Sianna Alcorn, and Ira Tager (2008). Ambient Ozone Concentrations Cause Increased Hospitalizations for Asthma in Children: an 18-Year Study in Southern California. Environmental Health Perspectives 116(8): 1063-1070.

Moorman, Jeanne E., Rose Anne Rudd, Carol A. Johnson, Michael King, Patrick Minor, Cathy Bailey, Marissa R. Scalia, and Lara J. Akinbami (2007). National Surveillance for Asthma --- United States, 1980—2004. Morbidity and Mortality Weekly Report: Surveillance Summaries. October 19. 56(SS08)1-14;18-54. Available at: http://www.cdc.gov/mmwr/preview/mmwrhtml/ss5608a1.htm (Accessed July 16, 2009).

Naureckas, Edward T., Vanja Dukic, Xiaoming Bao and Paul Rathouz (2005). Short Acting β-Agonist Prescription Fills as a Marker for Asthma Morbidity. *Chest* 128:602-605.

Neukirch, Francoise, Claire Segala, Yvon Le Moullec, Myriam Korobaeff, and Michel Aubier (1998). Short-term effects of low-level winter pollution on respiratory health of asthmatic adults. *Archives of Environmental Health*. 53(5): 320-9.

NIH (1997). *Practical Guide of the Diagnosis and Management of Asthma*. U.S. Department of Health and Human Services Public Health Service National Institutes of Health National Heart, Lung, and Blood Institiute. Publication No. 97-4053; October 1997.
http://www.nhlbi.nih.gov/guidelines/asthma/asthgdln.pdf

Ostro, Bart D., Michael Lipsett, Matthew B. Wiener, and John Selner (1991). Asthmatic Responses to Airborne Acid Aerosols. *American Journal of Public Health*. 81: 694-702.

Peters, Annette, Inge F. Goldstein, Ulrich Beyer, Kathe Franke, Joachim Heinrich, Douglas Dockery, John D. Spengler, and H. Erich Wichmann (1996). AAcute Health Effects of Exposure to High Levels of Air Pollution in Eastern Europe.@ *American Journal of Epidemiology*. 144(6): 570-81.

Pitard, Alexandre, Abdelkrim Zeghoun, Annabelle Courseaux, Jackie Lamberty, Veronique Delmas, Jean Luc Fossard, and Herve Villet (2004). Short-term Associations Between Air Pollution and Respiratory Drug Sales. *Environmental*

Research 95: 43-52.

Pope, C. Arden, Douglas W. Dockery, John D. Spengler, and Mark E. Raizenne (1991). Respiratory Health and PM10 Pollution. *American Review of Respiratory Disease.* 144: 668-674.

Schabenberger, Oliver and Carol Gotway. (2005). *Statistical Methods for Spatial Data Analysis*. New York: Chapman & Hall.

Schwartz, Joel (1994). Air Pollution and Hospital Admissions for the Elderly in Birmingham, Alabama. *American Journal of Epidemiology*. 139 (6): 589-98.

Schwartz, Joel, David Wypij, Douglas Dockery, James Ware, Scott Zeger, John Spengler, and Benjamin Ferris, Jr. (1991). Daily Diaries of Respiratory Symptoms and Air Pollution: Methodological Issues and Results. *Environmental Health Perspectives*, 90: 181-187.

Simon, Nathalie, B., Charles W. Griffiths, and Tracey Woodruff (2002). Air Pollution and Asthma in San Francisco: The Effects of Short-term Exposure on Asthma Medication Use, paper prepared for the 2nd World Congress of Environmental and Resource Economists, Monterey, CA June 27.

Sunyer, Jordi, Marc Saez, Carles Murillo, Jordi Castellsague, Francesc Martinez, and Josep M. Anto (1993). Air Pollution and Emergency Room Admissions for Chronic Obstructive Pulmonary Disease: A 5-year Study. *American Journal of Epidemiology*. 137(7): 701-5.

USEPA (2008). Final Ozone NAAQS Regulatory Impact Analysis. Office of Air Quality Planning and Standards, Health and Environmental Impacts Division. EPA-452/R-08-003. Available at: http://www.epa.gov/ttn/ecas/ria.html#ria2007.

USEPA (2006). Final Particulate Matter NAAQS Regulatory Impact Analysis. Office of Air Quality Planning an Standards. October 6. Available at: http://www.epa.gov/ttn/ecas/ria.html#ria2007.

Von Klot, S., G. Wolke, T. Tuch, J. Heinrich, D.W. Dockery, J. Schwartz, W.G. Kreyling, H.E, Wichmann, and A. Peters (2002). Increased asthma medication use in association with ambient fine and ultrafine particles. European Respiratory Journal 20: 691-702.

Walters, Sarah ,R.K. Griffiths, J.G. Ayers (1994). Temporal Association Between Hospital Admissions for Asthma in Birmingham and Ambient Levels of Sulphur Dioxide and Smoke. *Thorax*, 49: 133-140.

Zeghnoun, Abdelkrim, Pascal Beaudeau, Fabrice Carrat, Veronique Delmas, Onealy

Boudhabhay, Francois Gayon, Dominque Guincetre, and Pierre Czernichow (1999). Air Pollution and Respiratory Drug Sales in the City of Le Havre, France, 1993-1996. Environmental Research, Section A, 81: 224-230.