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Exposure to toxic pollution in new york state, 1998

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Abstract

The purpose of our study is to estimate the relationship between a New York State census tract''s exposure to toxic industrial pollutants and various socioeconomic variables. Our measure of exposure takes into account not only the distance between each pollution source – census tract pair, but ours is the first such study to use a measure that also incorporates meteorological conditions, including wind direction, wind speed, and air temperature. The measure is based upon a model of air pollution dispersal, the Gaussian Plume Model (GPM). We find that urban areas with large African American, working-aged populations, and those with relatively high education levels but low incomes experience the greatest levels of exposure to industrial pollution.

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1. Introduction

The purpose of our paper is to calculate the exposure of census tracts to industrial pollution and to examine how that exposure varies across socio-economic groups. This is a valuable exercise from a policy perspective; the results of our study can inform a normative discussion on environmental equity and guide environmental and industrial policies.

This paper addresses, in part, the question of how to calculate pollution exposure. In this respect, it is an extension of Hanna (2007, 2008) that use Toxic Release Inventory (TRI) data from the Environmental Protection Agency (EPA) together with weights that are Gaussian in the distance between the receptor (a census tract) and the pollution emitter (a TRI facility) to get a weighted sum of emissions from all facilities that surround a census tract. The other purpose of our paper is to use regression analysis to examine how exposure varies across census tracts with different socio-economic characteristics. Thus, this is similar to the work of Brooks and Sethi (1997) that looks at differences in exposure throughout the United States for the years 1988 through 1992. They calculate pollution exposure as the weighted sum of emissions produced within a 30-kilometer radius of a zip code's centroid. They measure distance to the centroid of the zip code where the pollution was produced while we use data on the precise latitude and longitude coordinates of the polluting facility and of the centroid of the census tract to calculate distances.

We use a model of pollution dispersal that takes into account how dispersal is affected by wind direction, wind speed, and air temperature. To our knowledge, this is one of the most sophisticated calculations of pollution exposure that has been used in the literature. Currently we limit our study to census tracts in New York State and use TRI data from 1998.[1] Hanna (2007, 2008) attempt to estimate the causal relationships between industrial pollution and prices (wages and property values), and incomes. The current study is purely descriptive. We find that urban areas with large African American, working-aged populations, and with relatively low incomes experience the greatest levels of exposure to industrial pollution.

In the next section we describe how we calculate pollution exposure and compare this approach to others used in the current literature. Next we describe in detail the pollution and socio-economic data that are used in this study. In the following section we present our estimates of how pollution exposure varies across socio-economic groups in New York State. Section 5 concludes.

[1] Although more recent TRI data are available, we chose this year because the most recent Census data that we have are for 2000 and we wanted to allow for a lag in how environmental conditions affect communities.

2. Measuring pollution exposure

It is normally quite difficult to obtain objective measures of environmental conditions. Given this, researchers usually use distance from the pollution source as a proxy for exposure to risk. However, as shown by Cameron (2006), not allowing for "directional heterogeneity in distance effects" can lead to biased results. This will be relevant when, for example, exposure to air emissions from point sources is affected by prevailing wind patterns. Cameron (2006) estimates a hedonic property value model that allows for directional heterogeneity in the effect of distance from a Superfund site on house prices in nearby communities. For this purpose, she uses the following regression model:

$$Y_i = \alpha + (\beta + \gamma_1 \cos\theta_i + \gamma_2 \sin\theta_i) d_i + \varepsilon_i \qquad (1)$$

where d is distance between the site and a house, and θ is the direction of the site from a house (measured in radians counter-clockwise from due east), so this allows for a difference in the effect of distance on Y (prices) depending upon the east-west coordinate of the property ($\cos(\theta)d$) and the north-south coordinate of the property ($\sin(\theta)d$) (where the site is the origin of measurement). Using house price data around a Superfund site in Woburn, Massachusetts between 1988 and 1996, the study finds that, in the absence of directional heterogeneity, the estimated price – distance relationship is statistically insignificant but, once allowed for, there are statistically significant differences in the estimated effect of distance on price in different directions from the site.

Apart from Cameron (2006), there are no other studies that allow for directional heterogeneity in the effects of environmental disamenities. Our study allows for such heterogeneity but does so by using data on wind patterns to calculate air pollution concentrations. We use this approach because our study incorporates many air pollution sources; we use data for 760 TRI facilities. In addition, we want to allow for other weather conditions that are likely to affect exposure levels, including wind speed and air temperature. We will now present this exposure calculation.

We use the Gaussian Plume Model (GPM) to produce a value for each New York state census tract's exposure to air emissions from industrial sites located throughout New York State. The GPM is the most frequently used atmospheric dispersion model. It assumes that a pollutant is carried downwind in a plume from its source and that the concentrations of the pollutant at different distances downwind are highest on the horizontal and vertical midlines of the plume. The distribution of the pollutant about these midlines is assumed to be Gaussian.

In this model, a key assumption is that, over short periods of time (e.g. a few hours) steady state conditions exist with regard to air pollutant emissions and meteorological changes. Air pollution is represented by a plume coming from the top of a stack of some height and diameter. As the gases are heated in the source plant the hot plume will be thrust upward some distance above the top of the stack to the 'effective stack height'. This effective stack height will depend upon the exit velocity of the gas, its temperature, and the temperature of the surrounding air.

Once the plume has reached its effective stack height it will be dispersed in three dimensions. Dispersal in the downwind direction depends upon the speed of the wind blowing across the plume. Dispersal in the crosswind direction and in the vertical direction is assumed to take the form of a normal Gaussian curve, with the maximum concentration at the center of the plume. See figure 1 for an illustration. Dispersion along these dimensions will depend upon a measure of the relative stability of the surrounding air. The algorithm used to calculate concentration of air emissions is as follows:

$$C(x,y,z) = \frac{Q}{2\pi U \sigma_y \sigma_z} \left\{ exp\left(\frac{-(z-h)^2}{2\sigma_z^2} \right) + exp\left(\frac{-(z+h)^2}{2\sigma_z^2} \right) \right\} \left\{ exp\left(\frac{-y^2}{2\sigma_y^2} \right) \right\} \quad (2)$$

where C(x,y,z) is the concentration of the emission (in grams per cubic meter) at any point x meters downwind from the source, y meters laterally from the center of the plume, and z meters above ground level. Q is the quantity or mass of the emission, in grams per hour. U is the wind speed (in meters per hour). h is the effective stack height above ground level, in meters. σ_y, σ_z are the standard deviations of a statistically normal plume in the lateral and vertical dimensions, respectively, and these depend upon downwind distance, x.[2]

The second term in brackets represents the distribution of the emissions in the vertical dimension. This is not symmetric around z equal to h because of surface reflection. That is, the plume cannot penetrate the ground, so there will be a relatively high concentration of the pollutant close to ground level.[3]

We calculate concentrations at ground level, z=0. So equation (2) becomes:

$$C(x,y,z) = \frac{Q}{\pi U \sigma_y \sigma_z} \left\{ exp\left(\frac{-h^2}{2\sigma_z^2} \right) \right\} \left\{ exp\left(\frac{-y^2}{2\sigma_y^2} \right) \right\} \quad (3)$$

3. Data

The New York State data we use are the 2000 census data from the US Census Bureau and the EPA's 1998 Toxics Release Inventory (TRI). We use the TRI data to calculate exposure to pollution for each census tract in New York State. The census data provide the latitude and longitude coordinates of the census tract centroid. The TRI

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[2] I present the formulae for the parameters σ_y, σ_z, and h in appendices I and II.

[3] Technically, this ground reflection of the pollutant is modeled by pretending that there is a 'virtual' source of the pollutant (in addition to the actual source) that is h meters below ground level. Then the probability distribution of the emission along dimension z is calculated as the sum of these two distributions: $\frac{1}{\sqrt{2\pi\sigma_z^2}} \left\{ exp\left(\frac{-(z-h)^2}{2\sigma_z^2} \right) \right\}$ (actual, at height h meters above ground) and $\frac{1}{\sqrt{2\pi\sigma_z^2}} \left\{ exp\left(\frac{-(z+h)^2}{2\sigma_z^2} \right) \right\}$ (virtual, at height h meters below ground). For z 'small' and positive (above ground level) the actual and virtual distributions will overlap, resulting in a higher calculated concentration of the pollutant than in the case of the absence of the second term.

provides the latitude and longitude coordinates for each TRI facility in New York State.[4] Hourly data for wind direction comes from the National Oceanic and Atmospheric Administration (NOAA). Using these, we calculate the down-wind (x) and lateral (y) distances of each census tract from each TRI facility.[5] We also get the hourly data for U, wind speed, from NOAA.[6] (See appendix I and II for an explanation of how we calculate h, the effective stack height, and σ_y and σ_z.) For each of the 760 TRI facilities in New York State in 1998, we take the reported emissions of all chemicals to the air for that year, converted to grams weight, and divide by 8,760 (the number of hours in a year) to get an estimate of emissions per hour, Q. We use these in equation (3) above to calculate the per-hour exposure of each census tract to emissions from each TRI facility. We then sum across all hours in 1998 and across all facilities in New York State to get a measure of annual exposure to TRI emissions (in grams per cubic meter) for all 4,907 census-tracts in New York State.[7] We have a complete set of data for 730 TRI facilities.

Our regression model takes the natural log of this annual exposure value and regresses it against socio-economic variables. We use the percent of the population that lives in an urban area; the percent that is Hispanic and African American; the percent that is aged 17 years or less and the percent that is aged 65 years or more; the percent living in poverty; the natural log of median household income, and the percent of occupied housing units that are rental units.

The descriptive statistics for these variables are given in table 1. Table 2 lists the 20 New York State counties with the highest levels of calculated exposure to TRI emissions, where total exposure is calculated as the sum of exposure across all census tracts in the county. Comparing this to table 3, which lists the 20 counties with the largest levels of TRI emissions *produced* within their borders, one can see that the rankings change depending upon whether one is measuring the production of emissions or the exposure to emissions. Across the 62 New York State counties, the correlation coefficient between the exposure rankings and the production rankings is 0.55. For

[4] We noticed that the TRI latitude and longitude data for many facilities were obviously wrong. For example, in some cases they implied that the facility was located in the Atlantic Ocean. Thus, we crosschecked and corrected these data, if necessary, using the mailing address of the facility (provided by the TRI) and the online latitude/longitude look-up search engine at http://geocoder.us/.

[5] x does not directly appear in equation (3). However, σ_y and σ_z are both increasing in x. See appendix II.

[6] In addition to data on U, wind speed, and wind direction, NOAA also provides data on air temperature that we use to calculate effective stack height, as we point out in appendix I. We need to have data on these meteorological conditions at each of the 730 TRI facilities. However, these are not available. We do have data for these conditions at each of 47 weather-monitoring stations located throughout New York State and the parts of Vermont, Massachusetts, Connecticut, New Jersey, Pennsylvania, and Canada that border New York State. Using inverse-distance-squared weights, we interpolate wind speed, wind direction, and air temperature at each of the 730 facilities using the readings from the 47 monitors. As a check, we use this method to interpolate weather conditions at each of these monitors using the actual readings from all of the other 46 monitors. We find that the correlation coefficients between the actual and interpolated weather conditions (across all 47 monitors and all 8,760 hours in the year) are 0.7, 0.98, and 0.62 for wind speed, air temperature, and wind direction, respectively.

[7] Since our weather data vary by hour, and there are 8,760 hours in a year, and we need to calculate exposure for each census tract (there are 4,907 in New York State) and each TRI facility (we have a complete set of data for 730 facilities), then our computer program is required to carry out 8,760 x 4,907 x 730 calculations, which is approximately 31.4 billion pollution exposure calculations.

example, Chautauqua and Rockland counties rank in the top 5 for production of emissions but are ranked 19th and 17th, respectively, for exposure to emissions.[8]

Table 3 presents the results of regressing the natural log of annual per capita pollution exposure on various community characteristics.

4. Regression Results

We present our OLS regression results in table 3. While there are 4,907 census tracts in New York State, we have a complete set of census data for 4,796 of them. The estimates suggest that, ceteris paribus, a 1-percentage point increase in the proportion of the population that is living in an urban area is associated with a 1 percent increase in exposure to TRI emissions.[9] (The urban variable is measured in percentage points while all of the other proportion variables are in decimal form.) Interestingly, a larger Hispanic population is associated with less exposure to pollution while a larger African American population is associated with greater exposure to pollution. That is, a 1-percentage point increase in the proportion of the population that is Hispanic/Latino is associated with a 0.6 percent reduction in exposure. The estimated change in exposure for a 1-percentage point increase in the proportion of the population that is African American is an increase of 0.9 percent. Populations that are relatively young (with a larger proportion of persons aged 17 years or less) or relatively old (with a larger proportion of persons aged 65 years or more) are less exposed to pollution than those that are mostly of working-age. The estimates suggest that, for a 1-percentage point increase in those young and old populations, the associated change in exposure to pollution is a reduction of 0.9 percent and 0.8 percent, respectively.

Interestingly, an increase in the proportion of a census tract's population that has only a high school education is associated with a reduction in exposure (a 0.8 percent reduction for every 1-percentage point increase in the high school educated population) while an increase in the proportion that has a college or graduate education is associated with an increase in exposure to pollution (a 1.2 percent *increase* for every 1-percentage point increase in the college-educated population). This may be due to a demand for an educated workforce by the industries that create the emissions.

Not surprisingly, an increase in the share of persons engaged in the manufacturing industry is associated with an increase in exposure to pollution. The magnitude of the parameter is striking; for a 1-percentage point increase in the share of all employed persons that are in the manufacturing industry, there is an estimated increase in exposure to pollution of 3,411 percent.

Finally we turn to measures of affluence and income distribution. An increase of 1-percentage point in the number of persons living below the poverty line is associated with a decrease in exposure to pollution of 0.9 percent. We use a quadratic in the natural log of income. The linear parameter estimate is positive and the quadratic parameter

[8] These two counties are located along the border of New York State. Due to prevailing winds, it is likely that they have greater exposure to emissions from facilities in Ohio and Pennsylvania rather than those in New York State. Future work will incorporate emissions data from facilities in states bordering New York State. See the map of New York State counties in figure 2.

[9] Since the dependent variable is the natural log of exposure to pollution, for all parameter estimates β (except those for the natural log of median income) we interpret (exp(β) -1)*100 as the percentage change in exposure that is associated with a 1-unit change in the independent variable.

estimate is negative. However, for the range of values in our sample, pollution exposure is predicted to fall monotonically with higher income. For example, for the average value of the natural log of income (10.63, which corresponds to a dollar income value of $41,357) the predicted effect of a 1 percent increase in income (an increase in the natural log of income from 10.63 to 10.64, which corresponds to a dollar income value of $41,773) is associated with a reduction in pollution exposure of 1.8 percent. Thus, we have the interesting result that both a greater proportion of the population that is at the bottom of the income distribution and a higher median income are associated with better environmental conditions.

The last explanatory variable that we use is the share of occupied housing units that are rental units. Here the estimated relationship is negative; for a 1-percentage point increase in the share of rental units our measure of air quality improves by 0.8 percent.

Taken as a whole, the results suggest that the census tracts in New York State that are most exposed to industrial pollution are those that are urban, whose residents are predominantly African American, between the ages of 18 and 64 years, are engaged in the manufacturing sector, are college-educated, with low incomes but relatively low poverty rates, and with housing units that are mostly owner-occupied.[10]

Some of these estimates have the opposite sign to those found by the Brooks and Sethi (1997) study. They found that, for the United States as a whole and for the years 1998 through 1992, greater educational attainment (for both high school and college) is associated with lower exposure levels. They also find that both a higher percentage of renter-occupied housing and a higher poverty percentage were associated with poorer environmental conditions. The main difference between the Brooks and Sethi measure of pollution and the measure used here is that the former explicitly takes into account the relative toxicities of various chemicals that are emitted. This study treats a pound of each chemical equally. Thus, in future work we will use a toxicity-weighted sum of emissions, while also taking into account weather conditions. Note that the Brooks and Sethi paper uses weights that are linear in distance and that become zero for a distance equal to or greater than 30 kilometers. In addition, their unit of analysis is the zip code (rather than the census tract). They sum all emissions that are produced within a given zip code and then take into account distance to the centroid of the zip code where the emission originated, rather than using information on the precise location of each polluting facility, as we do.

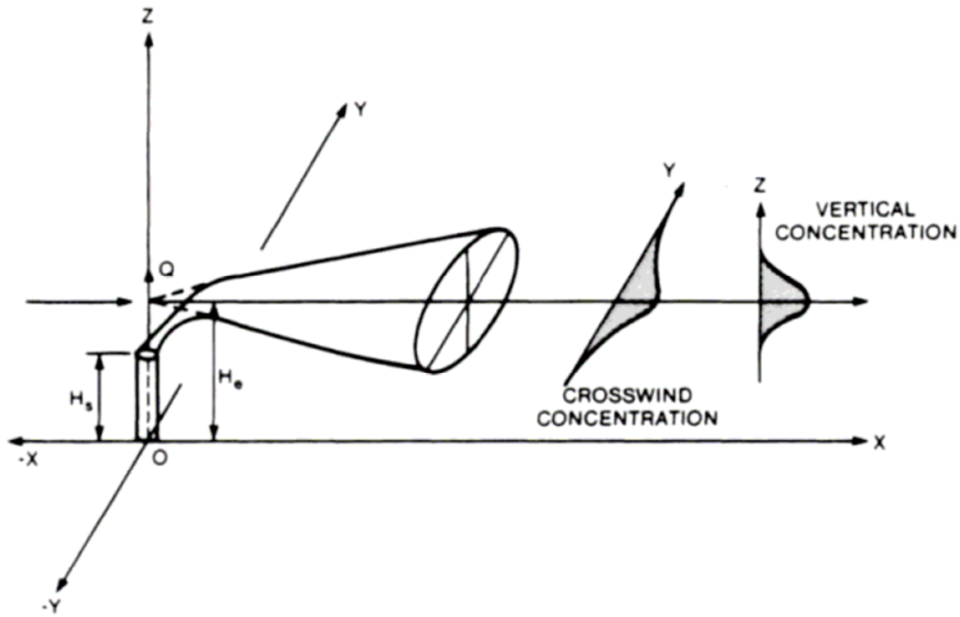
[10] We used the same set of explanatory variables in a regression model with a simpler measure of exposure as the dependent variable. That was the weighted sum of emissions from all polluting facilities in New York State, where the weight is the inverse of the squared distance between the census tract and the facility. Those estimates are not presented here, in the interests of space. The main differences, compared to table 4, are that the Hispanic and 'Aged 65 or more' parameter estimates become statistically insignificant and the sign of the 'Occupied housing units that are rented' parameter estimate becomes positive. While the signs of 'Aged 17 or less', 'High School degree only', and 'Bachelors or Prof/Graduate Degree' parameter estimates remain the same, they are statistically significant at only the 9 percent level. Thus, taking into account wind directions and other relevant weather conditions does affect the conclusions that one might draw from the analysis.

5. Conclusion

This study uses the Gaussian Plume Model (GPM) to calculate the exposure of census tracts in New York State to TRI emissions from facilities throughout that state. This is the first study to use this relatively sophisticated method of computing exposure. The main advantage to using this is that it explicitly takes into account wind speed and wind direction when determining which locations are exposed to a given polluting facility's emissions. We then use these exposure data to estimate the relative exposure of various socio-economic groups to industrial emissions.

Our results suggest that urban areas with large African American, working-aged, and relatively well-educated populations, and with relatively low incomes will experience the greatest levels of exposure. Further, it seems that accounting for wind patterns does significantly affect our results. Future work will take into account the relative toxicity of the various chemicals that are emitted.

Figure 1. Gaussian plume distribution



Note: H_s is the height of the stack, H_e is the effective stack height, x is the distance downwind.
Source: Chapter 10, Harrison (2001)

Figure 2. New York State counties

Source: www.census.gov.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Pollution Exposure, grams per cubic meter	2.76	13.86	0.07	523.48
Per Capita Pollution Exposure, grams per cubic meter	0.001	0.008	0.000	0.390
ln (Per Capita Pollution Exposure)	-8.17	1.31	-11.35	-0.94
% Urban	87.66	29.85	0	100
% Hispanic	0.15	0.19	0	1
% Af. American	0.19	0.28	0	1
% Aged 17 or less	0.25	0.07	0	0.63
% Aged 65 or more	0.13	0.06	0	0.92
% High School Degree Only	0.28	0.09	0	1
% Bachelors or Prof/Graduate Degree	0.25	0.17	0	1
% of Workforce in Manufacturing	0.10	0.07	0	1
% in Poverty	0.15	0.13	0	1
Median Household Income	46,452.84	23,146.45	2,499	200,001
ln(Median Household Income)	10.63	0.49	7.82	12.21
% of Occupied Housing Units that are Rented	0.46	0.29	0	1
Sample Size	4,796			

Source: EPA's Toxic Release Inventory, 1998 and the US Census Bureau, 2000. Data are for New York State.

Table 2. Top 20 Counties in New York State, Ranked by 1998 *Exposure to* Air Emissions

Total Exposure to Air Emissions	% of State Total	County
6198.33	46.74	Monroe County
1735.23	13.08	Erie County
891.06	6.72	Onondaga County
393.40	2.97	Queens County
368.38	2.78	Kings County
280.28	2.11	Orange County
255.17	1.92	Bronx County
219.95	1.66	Schenectady County
219.51	1.66	New York County
218.53	1.65	Albany County
190.43	1.44	Niagara County
173.46	1.31	Oneida County
169.53	1.28	Suffolk County
166.33	1.25	Westchester County
147.89	1.12	Nassau County
133.12	1.00	Broome County
132.29	1.00	Rockland County
130.66	0.99	Saratoga County
118.07	0.89	Chautauqua County
117.38	0.89	Rensselaer County

Note: The 'total' statistic is the sum of the exposure measure across all census tracts in the county. Annual Exposure data are measured in grams per cubic meter.
Source: Toxic Release Inventory (TRI) of the EPA, 1998 and authors' calculations.

Table 3. Top 20 Counties in New York State, ranked by 1998 *Production* of Air Emissions

Total Air Emissions, pounds weight	% of State Total	County
8,409,664	21.93	MONROE
5,603,852	14.61	ERIE
4,331,400	11.29	CHAUTAUQUA
4,142,481	10.80	ORANGE
1,615,763	4.21	ROCKLAND
1,457,150	3.80	ST LAWRENCE
1,003,484	2.62	YATES
991,633	2.59	BROOME
944,280	2.46	SUFFOLK
834,119	2.17	ONONDAGA
781,257	2.04	NIAGARA
766,816	2.00	SARATOGA
639,487	1.67	NEW YORK
577,203	1.50	LEWIS
574,441	1.50	ALBANY
548,757	1.43	SCHENECTADY
514,962	1.34	QUEENS
471,553	1.23	WAYNE
379,500	0.99	GREENE
350,947	0.92	CHENANGO

Note: The ‘total’ statistic is the sum of emissions to the air from all facilities in the county, in pounds weight.
Source: Toxic Release Inventory (TRI) of the EPA, 1998.

Table 4. OLS Regression Results, Dependent Variable: Natural Log of Per Capita Annual Pollution Exposure

Intercept	23.77**
	(5.75)
% Urban	0.01**
	(0.00)
% Hispanic	-0.98**
	(0.13)
% Af. American	0.63**
	(0.08)
% Aged 17 or less	-2.37**
	(0.32)
% Aged 65 or more	-1.52**
	(0.32)
% High School Degree Only	-1.84**
	(0.34)
% Bachelors or Prof/Graduate Degree	0.77**
	(0.24)
% of Workforce in Manufacturing	8.13**
	(0.28)
% in Poverty	-2.37**
	(0.41)
ln(Median Household Income)	-4.16**
	(1.08)
Square of ln(Median Household Income)	0.11*
	(0.05)
% of Occupied Housing Units that are Rented	-1.44**
	(0.12)
R-Squared	0.298
Adjusted R-Squared	0.296
Sample Size	4,796

** denotes statistical significance at the 1 percent level. Standard errors in parentheses.

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Appendix I

Effective Stack Height, h

h is defined as the height of the stack that is emitting pollutants, h_s, plus the plume rise, ΔH, which is the height above the point of emission (stack opening) reached by the plume due to its buoyancy, as the plume is usually warmer than the surrounding air.

$h = h_s + \Delta H$.

Thus, h requires us to calculate plume rise, which depends upon the rate of heat emission from the stack, Q_h:

$Q_h = 66.8 d^2 v \left(\frac{T_s - T_a}{T_s} \right)$ where T_s is the temperature of the stack, T_a is the air temperature, d is the diameter of the stack, and v is velocity of the emission from the stack.

Then $\Delta H = \frac{1}{4} Q_h^{1/3} h_s^{2/3} U$ where h_s is the height of the stack and U is the wind speed at the stack height. See Harrison (2001) and Vallero (2008) for further details.

We received data for T_s, v, d, h_s from the EPA's TRI and these vary by SIC (Standard Industrial Classification) code only; they are not TRI facility-specific. Data for U and T_a are from the National Oceanic and Atmospheric Administration (NOAA).

Appendix II

Standard Deviations of the Plume in the lateral & Vertical Directions, σ_y, σ_z

σ_y and σ_z are determined by prevailing atmospheric turbulence. Turbulent motions in the atmosphere vary in size and intensity and the greater their size/intensity the more rapid is the plume growth and, hence, the less concentrated the pollutant becomes. Small scale turbulent motions tend to dominate the plume growth close to the point of emission, where the plume is relatively small, and larger scale turbulent motions (or eddies) dominate at greater distances. Thus, σ_y and σ_z increase in value with distance from the pollution source. They are calculated as:

$\sigma_z = ax^b$

$\sigma_y = 465.11628 x (\tan \Theta)$ and $\Theta = 0.017453293 (c - d \ln(x))$

Θ is measured in radians. x is in kilometers. σ_y and σ_z are in meters. The parameters a, b, c, and d depend upon how stable turbulent motions are; that is, they depend upon atmospheric stability. Given prevailing weather conditions in New York State, the appropriate atmospheric 'stability class' for our study is such that a, b, c, d take on the values 109.3, 1.0971, 18.333, and 1.8096, respectively. See Harrison (2001) and Vallero (2008) for further details.