The needs of the Army: using compulsory relocation in the military to estimate the effect of air pollutants on children's health*

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Abstract: Recent research suggests that pollution has a very large impact on asthma and other respiratory and cardiovascular conditions. But this relationship and its implications are not well understood. I use changes in location due to military transfers, which occur entirely to satisfy the needs of the army, to identify the causal impact of pollution on children's health outcomes, measured by respiratory hospitalizations. I use individual-level data of military families and their dependents, matched at the zip code level with pollution data, for the major air pollutants for the period 1989-1995. I find that for military children only ozone appears to have an adverse effect on health. There are several methodological findings of interest. Models that look at the effects of a single pollutant at a time can be very misleading. Moreover the data supports the idea that interactions between pollutants (which are rarely used) have a statistically significant effect on health. I find evidence that measurement error in pollution predictions is not random and has large effects on the estimated coefficients. Lastly I look at whether the effects of pollution on children's health vary depending on the socio-economic characteristics of their parents, as suggested by previous epidemiological studies. I find that the effects of ozone appear to be greater for children of higher SES.

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I. Introduction

Recent research suggests that pollution has a very large impact on asthma and other respiratory and cardiovascular conditions (WHO 2003). But little is known about whether these effects are truly causal. Using conventional data sets, it is difficult to separate the effects of pollution on health from the effects of socio-economic background; poor and disadvantaged families often live in polluted areas whereas wealthier families can afford to move to cleaner areas. Polluting factories will also locate in areas where land is cheap and constituents have low political leverage. High pollution areas often have higher crime, less availability of public services, and different average socio-economic characteristics. On the other hand families in worse health are more likely to move away from polluted areas (Coffey 2003).

I use changes in location due to military transfers to identify the causal impact of pollution on children's health outcomes, measured by children's hospitalizations. The military ordinarily requires that its members move to different locations in order to satisfy the needs of the army. These relocations are frequent, somewhere between 24 and 48 months, and they affect all enlisted men and their families: about 1/3 of army families experience a Permanent Change of Station (PCS) in a given year.[1] Families are moved to high or low pollution areas in a manner that is independent from their socio-economic characteristics: this unusual characteristic of the military provides us with a unique quasi-natural experiment:

Most military families live on military bases. Bases provide many services, including childcare, school, entertainment and health care. Even though there are differences among bases (e.g. weather), the variation in the environment that military families experience when they move is small (relative to civilian families), so that unobserved neighborhood characteristics are not likely to be a large source of bias. There are other advantages to studying the military. All enlisted personnel and their dependents are

[1] This is about four times the relocation rate of civilians. See Griffith et al (1988).

covered by military health insurance (Champus/Tricare),[2] which is quite generous (no premiums, low deductibles[3]), and is highly rated by its members.[4] Therefore, issues of access to care due to income are not first-order concerns. Lastly, since information on hospitalizations and doctor visits is available for all causes, hospitalizations from causes that are unlikely to be correlated to pollution can be used to confirm the findings: they should not be affected by pollution levels.

I use individual-level data on military families and their dependents, matched at the zip-code level, with pollution data for the period 1989-1995. The data contain information on children, which are of particular interest. Previous research suggests that children are more at risk than adults, and that they tend to develop symptoms faster. The cost of pollution associated with detrimental health effects on children is also presumably large since they will be experienced over a lifetime.

There is a vast literature in epidemiology that documents strong correlations between pollution and mortality (e.g. Pope et al, 2002; Samet et al, 2000), and between pollution and other health measures (WHO 2003). Two recent papers in economics (Chay and Greenstone, 2003; Currie and Neidell, 2005) look at the effects of pollution on infant mortality using plausibly exogenous time-series variation to identify the effects of pollution on infant mortality.[5] The identification strategy used in this paper uses cross-sectional (and time-series) variation in pollution, and argues that, in the military, individual exposure to pollution is independent of individual- and site-specific characteristics. This identification strategy overcomes the two potential issues with these previous studies. One is that seasonal variation in pollution may be accompanied by changes in other variables that may affect health (for example the decrease in pollution studied by Chay and Greenstone was induced by a recession which was accompanied by

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[2] Eligibility under Tricare as of 2003: The Tricare programs are available to family members of active-duty military service personnel and also to military retirees and their dependents. These dependents include spouses, former spouses, children and stepchildren. Spouses must not be covered by an employer-sponsored health plan. Former spouses remain eligible unless they remarry. Unmarried children under age 21, and unmarried children under age 23 who are full-time students are eligible. Children remain eligible if the parents are divorced or remarried. Stepchildren lose eligibility after a divorce unless adopted by the sponsor. Eligibility may extend past age 21 if the child is severely disabled and the condition existed prior to age 21, or if the condition occurred between the ages of 21 and 23 while the child was a full-time student.

[3] See footnote 10 for details on deductibles and co-pays under Champus.

[4] In 1995, 70% of spouses reported being satisfied with the Army Medical System.

[5] Similarly, Jayachandran (2005) looks at the effect of PM on infant mortality using changes in PM induced by fires in Indonesia.

reductions in income and employment). Second, families may move as a result of high pollution levels.

There are several more contributions. I include measures for 5 major pollutants in the US, and investigate several specification issues, including the effects of omitting pollutants from the model, the effects of measurement error, and the existence of interactions and non-linearities. Also I look at children ages 0 to 5, not just infants.

I find that for military children only ozone appears to have an adverse effect on health, measured by respiratory hospitalizations. The effect is large: the implied elasticity for the probability that a child is hospitalized for a respiratory condition with respect to O_3 is between 0.7 and 1.14. Alternatively, considering the effects of all pollutants jointly, I find that moving from an area where all pollutants are high to a low pollution area reduces the percentage of children hospitalized by as much as 77%. Importantly, these effects are only significant for children ages 2 to 5, and not for those ages 0 to 1. Furthermore, I find that the effects of ozone appear to be greater for children of higher SES. Both of these findings are consistent with the idea that ozone only affects those that spend a significant amount of time outdoors.

There are a number of additional findings. I used several methods to impute pollution at the zip code level, and test the sensitivity of the models to distance from monitors. This is important because monitors are not randomly located across the country. I find evidence that measurement error in pollution predictions is not random, and that it has large effects on the estimated coefficients. I find that models that look at the effects of a single pollutant at a time can be misleading. The results strongly suggest that non-linear models, and models that include interactions between pollutants (which are rarely used), are preferable to linear models. These results suggest reasons why previous studies differ in their findings.

The paper proceeds as follows. Section II describes the data used for the empirical analysis, and a number of data-related issues. Section III describes the relocation process in the military and provides evidence that relocations cannot be predicted using individual characteristics of the enlisted men. Section IV presents the empirical strategy and the main results. In Section V, I explore the functional form, issues of interpretation, and look at the effects of pollution by SES. Section VI concludes.

II. Data description and issues

A. military personnel data

The data were provided by the Defense Manpower Data Center (DMDC) under the Freedom of Information Act. It contains annual individual-level information on enlisted married men[6] and their dependents for the period 1988-1998,[7] including the characteristics of the enlisted men (age, race, education, occupation, rank, location, date of enlistment, date of last enlistment, total number of months of active service) and information on all hospitalizations (by condition) of their wives and children. Individuals' location is given by the zip code to which their sponsor is assigned to duty. Only information on individuals located in the Continental U.S. (48 contiguous states) was obtained. All characteristics are measured as of December 31st.

The data do not contain earnings, but contain almost all the variables that determine earnings, including rank, experience, family structure, and location. They do not include deployment compensation, performance bonuses, or spousal earnings. However these are small relative to household income.[8] Appendix A contains more details about the data.

B. Dependents' health data

[6] Married Army couples receive special consideration for relocation and therefore are also problematic. Most enlisted moms are single-parents and some have suggested they receive special considerations concerning relocations. Finally divorced parents are excluded since most likely their dependents do not live when them and are therefore not subject to relocations.
[7] Information on families was available starting in 1988.
[8] Furthermore, as was already mentioned above, there are very small differences in access to health care since all dependents are covered by generous insurance plans.

Military personnel and their dependents have access to care through two separate systems.[9] Military Treatment Facilities (MTFs) provide free care to all beneficiaries, subject to capacity.[10] Military families can also obtain care elsewhere through their health insurance. Generally beneficiaries are required to obtain care from an MTF if such care is available before using alternative care. The service area of an MTF generally includes zip codes within 40 miles of the facility. In 1995 MTFs served about 89% of military dependents. The Map in Figure 1 shows the locations of all the military installations (most of which are bases) and treatment facilities in my data for the Continental United States in 1990. Each circle represents an installation (the size of the circle is proportional to the number of observations in my data) and the triangles show the locations of the military treatment facilities.

The Civilian Health and Medical Program of the Uniformed Services (Champus) began in 1966. Under Champus, beneficiaries paid no premiums and were all subject to a single plan.[11] Starting in 1995 a new system known as TRICARE was phased in, replacing Champus. The main changes included the availability of different insurance plans (one of which is identical to Champus), and the introduction of managed care for the provision of care. Importantly, the eligibility criteria did not change at all during the 1989-1995 period.[12]

Health data are obtained from the administrative claims filed by these two separate sources: MTFs and insurance. MTFs only filed claims for hospitalizations—all other services obtained at MTFs are not observed. Starting in 1996 the data from MTF are no longer available. Because claims are reported in fiscal years (which begin October), the data for MTF hospitalizations in 1995 is incomplete: it is missing a quarter of that year's hospitalizations, which would have been reported in 1996. Thus because of the changes

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[9] This brief description and the related statistics come from two sources: the 1995 Rand report and Appendix X of the 1996 Department of Defense "Military Compensation Background Papers: Compensation Elements and Related Manpower Cost Items—Their Purposes and Legislative Backgrounds."

[10] There were about 117 military hospitals and 400 military clinics in 1995. Priority for access is given first to active duty personnel, then to their dependents and to others.

[11] The plan included small annual individual and family level deductibles ($100 per family if below E4 grade, $300 otherwise), a 25% co-pay for outpatient costs, and a $1000 family stop loss. There was a daily nominal inpatient cost (not exceeding $25 annually in 1994).

[12] Personal communication with Scott Seggerman at DMDC, September 2003.

in Champus insurance and the incomplete MTF data, the data for 1995 are to be treated with caution. CHAMPUS/Tricare claims exist for hospitalizations and for other services. Unfortunately CHAMPUS hospitalization claims do not report the diagnosis for the hospitalization.

I construct several outcome measures using these claims. The first measure is whether or not the person was hospitalized during the year (regardless or whether the hospitalization occurred in a military or private facility). The second is whether the person was hospitalized in an MTF.[13] For MTF hospitalizations, I construct indicators for whether a hospitalization was for a respiratory condition (ICD9 codes 460 to 519, 769-770 and 786[14]), an external cause (ICD9 800-999 or starting with "E"), or for any other cause.[15]

C. Pollution and weather data

Pollution data come from the Environmental Protection Agency (EPA). They contain annual summary statistics for the period 1988-1998 of measurements at the monitor level of the 6 major environmental pollutants in the US, namely: particulate matter of 10 micro meters in diameter (PM10), ozone (O_3), lead (Pb), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2).[16] Only monitors that appear in at least 8 years out 11 are kept, and the missing values were interpolated within monitors over the year to obtain a balanced panel of monitors.[17] The final number of monitors is reported in Appendix D. Background information on these 6 air pollutants, such as sources of emissions and suspected health effects, is given Appendix B.

[13] I can also calculate the number of hospitalizations. However this measure is somewhat less accurate, because hospitalizations are associated with multiple claims. Using the date of admission and of dismissal it is possible to define unique hospitalization events, but there are inconsistencies across claims (overlapping dates for example) that possibly reduced the accuracy of hospitalization counts.

[14] Diagnosis codes 769 and 770 are for infants only. Code 786 includes ill-defined conditions of the respiratory system.

[15] In all cases, a hospitalization occurs if the individual was admitted to the hospital and remained for at least one night.

[16] Unfortunately no measurements exist for PM2.5 (smaller particles) during this time period, which recent research suggests may be more directly related to health outcomes. It is also worth noting that NO2 concentration is most likely overestimated in these data: monitors measure NO_X and convert it into NO_2, and it is known that the conversion frequently overstates actual concentrations. Improved NO_2 data is not yet available from the EPA. Personal communication with Kevin A. Cavendier at the EPA.

[17] The data provided by the EPA contains an unbalanced panel of monitors for each pollutant. In calculating pollution levels for any given area, the addition and deletion of monitors are problematic, especially if the year-to-year variation within area is to be exploited. New monitors are usually added because the EPA learns of a source of emission. This generates a sharp increase in pollution from one year to the next at that location that isn't necessarily real. Conversely, monitors are often removed because the area is compliant (pollution levels are low). Predictions for the area that are calculated using remaining adjacent monitors will overestimate the pollution level. Therefore, following EPA's practice, a balanced panel of monitors was created.

Weather data (temperature, humidity and rain) from the National Climatic Center were also merged. Weather conditions are important potential confounders: for example very hot weather during the summer raises O_3 levels and may also result in more deaths. (See appendix A for more details.)

D. Assignment of pollution levels to individuals: some issues

For each individual in the data, we must estimate exposure to each pollutant using the pollution measurements obtained from monitors (located at a given longitude and latitude). This requires estimation of pollution levels for zip codes for which there are no monitors (the vast majority of zip codes). The simplest commonly used procedure is Inverse Distance Weighting (IDW), which assigns individuals the weighted pollution average of monitors within a given radius, using the inverse of the distance to the point as weights (as Currie and Neidell, 2005). Another simple option is to calculate county averages by averaging values across monitors in a given county (as Chay and Greenstone, 2003). Alternatively one can use Kriging. Kriging is a statistical method that estimates a model of spatial correlation and uses this model to generate predictions.[18] It consists in estimating the parameters that describe the spatial correlation between observations (like estimating ρ for an AR(1) model) and then using the estimates to find the predictions that minimize the sum of squared errors. Covariates may be used as well (in which case the method is referred to as co-Kriging). The relevant covariates included annual measures of weather[19] (rain, temperature, humidity and wind direction), terrain (altitude) and emission sources (which are not available for this period and therefore not included).

Kriging has several advantages over the alternative methods previously used by economists. (See Appendix C for a brief review of models of spatial correlation.) First, Kriging is the best linear unbiased predictor. Second, measures of fit can be obtained. Lastly, Kriging allows prediction for a much larger number of locations in the United

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[18] Statistical models of spatial correlation are closely related to time series models commonly used in economics. Kriging estimation is akin to Feasible Generalized Least Squares Estimation, except that observations are correlated across space (two dimensions) rather than time.

[19] Ozone exhibits strong seasonality within the year, increasing during the summer. I am ignoring this potential source of pollution variation. Seasonal variation in other pollutants is also ignored because some military data (duty zip code most importantly) could only be obtained annually.

States. Kriging predictions are based on the annual arithmetic mean at each monitor. Appendix E contains the details of the models that were used to generate Kriging predictions, and Appendix F shows the measures of goodness of fit for each pollutant and for every year.

All of these methods assume that distance from monitors is an important predictor of the level of pollution (i.e. that there is spatial correlation). I formally test this assumption in the data for every pollutant and every year using multiple statistics of spatial correlation (Moran's I, Geary's C and Getis & Ord' G; see Appendix C for a review of these measures). The results of these tests for 1988 are in Appendix D. In all cases the data strongly reject the hypothesis of no spatial correlation, providing support for the methods used here.

Maps for the Kriging predictions for each pollutant are in Figure 2. They show that in 1990, the highest (annual) concentrations of ozone were in California, and the states in the Mid-Atlantic, East North Central, and South East regions. For PM10, the highest levels are found in California and Arizona. NO_2 concentrations are highest in California and parts of Texas. SO_2 concentrations on the other hand are lowest in California and highest in Pennsylvania and New York. CO is highest in the Northwestern and Eastern United States. These patterns are similar to those observed today. Overall pollution levels tend to be higher in urban areas, but it is worth noting that the density of monitors is lower in rural areas. There is a significant amount of variation in pollution levels across the country, and this variation is different for each pollutant. Also note that the predictions for Pb are poor. (Pb has the fewest monitors and the lowest measures of fit of all pollutants; see Appendix F.)

I have also matched individuals to pollution levels using IDW (for both 15 and 30 mile radii) and county-level averages using number of observations per year by monitor as weights. In all cases, individuals are matched to the predictions in the zip code to which their sponsor is assigned to duty. Figure 3 shows national trends for all pollutants from

1988 to 1995 obtained using the various methods.[20] All prediction methods yield trends that closely follow the trends obtained from monitor data.[21] All pollutants show downward trends, with the exception of O_3, which decreases until 1992, and starts rising thereafter.

Matching individuals to pollution predictions in a precise geographic unit (in this case at the zip code level) might result in poor predictions of exposure, since individuals move around quite a bit, even given excellent predictions of outdoors pollution levels at the zip code level. I assume that for children this problem is not as important as for adults. However personal exposure will also depend on indoor pollution[22], as well as on individual behavior (mobility and time spent outdoors).

Figure 6 shows the distribution of pollutants for the final sample used in this study. The graphs document the variation in pollution that will often be used in the identification of pollution effects. Note that most pollutants have long thin right tails—there are very few observations for the highest pollution levels. Previous research has also suggested that there can be strong correlations between different pollutants, generally because of common sources. For example, NO_2, CO and PM10 are all generated by automobile engines. Table 3 shows the correlations in my data. The largest correlation is about 0.5, between PM10 and CO. Also interestingly, there is a negative correlation between O_3 and CO,[23] and between Pb and NO_2.[24] These correlations are not high enough to generate collinearity problems[25] but also not small enough so to think of these as independent regressors.

[20] The trends were calculated by averaging over the original monitor data, or alternatively averaging over all zip codes for which predictions were available.
[21] Although it is worth noting that Kriging predictions are always below pollution levels at the monitor sites. This is to be expected given that monitors are generally located in areas that are (or were) suspected to be polluted (in addition to highly populated areas).
[22] The relationship between outdoor and indoor pollution depends on penetration rates and on whether there are indoor sources of pollution, such as smoke. Studies have shown that the correlation between personal exposure and ambient measures is fairly high in the case of PM, and low in the case of O3 (indoor concentrations are about half). See WHO (2003).
[23] This has been observed in previous studies as well (e.g. Samet et al 2000).
[24] These correlations are based on spatial predictions and thus might quite different in reality. But since monitors for different pollutants do not overlap, the real correlations at particular locations are not known.
[25] I also examined whether there was significant multicollinearity by estimating auxiliary regressions predicting one pollutant as a function of the others. I did not find evidence of significantly high multicollinearity. Results available upon request.

Since military installations are more likely to be located in rural areas, it is possible that the military's exposure is not representative of the general population. To gauge this, I compute mean exposure for the population, by averaging predictions over zip codes and using the population ages 18 and below in the zip code as weights. (The population data come from the 1990 census STF 3A tapes.) I compare these averages with averages for military children 18 and below in my data. Appendix G presents the means for both populations over the entire study period. The military are exposed to lower pollution levels on average, although the difference is generally small (less than 1/2 of a standard deviation) except for NO_2. Overall, however, the exposure appears to be quite similar. Appendix H shows the trends in exposure for both populations. These are quite similar, although as suggested by the means, NO_2-levels are much lower for the military. Also it is worth noting that the trends for Pb are very variable, but Pb has the fewest monitors in the data and the lowest fit for the Kriging predictions. For this reason I will not look at the effects of Pb on health in this paper, although I do use Pb as a control in some specifications.

E. Sample and summary statistics

I keep children under age 5, from 1989 to 1995. (Recall there are no claims data from MTFs from 1996 forward.) The year 1988 is dropped because the health insurance claims data for that year appear to be incomplete (DMDC recommend 1988 be excluded from the analysis). To minimize differences in access to care, I exclude individuals with no access to a military hospital. Also I exclude officers, since it appears that they may have a greater ability to affect relocations, and stepchildren—they are less likely to live and move with their enlisted father. Finally I restrict the estimation sample only to those in bases for which the closest monitor is within 50 miles for all pollutants. Individuals with missing data were also dropped.

In 1989, there were a total of 769,741military personnel in the Army.[26] The final sample includes 68,676 married enlisted men with dependents stationed in the continental U.S.,

[26] Data available online from the Department of defense at http://web1.whs.osd.mil/mmid/mmidhome.htm

with exactly 20,779 men in 1989, about 2.7% of the Army for that year. This percentage is similar or higher (about 3.6% in 1995) in other years, except for 1990 and 1991. In these two years the sample is smaller because of deployments for the gulf war (recall that the data include only children whose fathers are stationed in the continental U.S.).[27]

Table 1a shows the summary statistics for the sample. About half of the children are male, and 60% are white non-Hispanic. On average, children can be followed for 3.2 years (if no distance to monitor restriction is made). Of those that are observed in consecutive years, about 30% move—the same percentage reported by the military for the Army at large. The enlisted sponsors (dads) are about 29 years of age on average, have been in active duty for about 9 years and they have between 2 and 3 dependents (including their spouse, so about 1.4 children), and 12% have at least some college education. For those observe in two consecutive years, about 2% increase their education and about 18% move up in rank.

The hospitalization data show that about 11% of children were hospitalized at least once in the previous year. This hospitalization rate is higher than that observed for children of civilian parents[28] but similar to what has been reported elsewhere for dependents of military personnel.[29] Most of these hospitalizations occur at an MTF. Among MTF hospitalizations (for which diagnosis codes are known), 26% are due to respiratory conditions. Figures 4 and 5 show the distribution of hospitalizations for all ages. It shows that hospitalization rates fall rapidly with age, bottoming out between ages 5 and 15, after which they start rising. Because these rates are so low and because young children are more susceptible to the immediate effects of pollution, I have restricted the analysis to children under age 5. Figure 5 suggests that children ages 0 to 1 exhibit a much larger

[27] There were 665,476 troops deployed during 1990-1991 for the desert Shield and Desert Storm operations.

[28] In the NHIS during the same years, the number is approximately 6% for children ages 0-5 of families with annual incomes below $40,000.

[29] In the Rand Report MR-407-1-OSD (Hosek et al, 1995), the percentage of dependents that were hospitalized overnight was about 8.5% in the early 1990s. This includes children over the age of 5, elderly persons, spouses and enlisted personnel (Table B.5). In Table 3, adjusting for covariates, the predicted percentage of dependents with a hospitalization is about 11.3%. In addition, this study only looks at those with the highest priority for MTF (free) care, who are more likely to use care than other dependents. There are several reasons including the differences in demographic characteristics of military and civilian families. But this is more likely due to the very generous insurance provided by the military, which prompted the introduction of Tricare. Rand (1995) reported that "After correcting for demographic differences and other factors (...) the rates at which military beneficiaries used inpatient and outpatient services were on the order of 30 to 50 % higher than those of civilians in fee-for-service plans."

rate of respiratory hospitalizations than children ages 2 to 5, so I analyze the effects of pollution separately for these two age groups.[30]

The remainder of the table shows the characteristics that are common to a base. There are 177 bases that appear in the study, although some of them are small and are not in the sample every year. Ultimately there are 940 base*year observations. The average base in the sample has about 6,100 married fathers, although there is a lot of variation across bases. Other base characteristics include distance to cities of varying size, distance to the closest MTF, and the number of Army personnel requesting that base in a given year as a first choice. These were collected to investigate the nature of relocations (see below). I report annual pollution means. I find that 18% of the sample has county predictions for all pollutants; 5% has IDW15 predictions for all pollutants, and IDW30 predictions exist for about 50% of the sample.

III. Describing relocations of military families

Military regulations require that enlisted personnel be relocated at least every three years, but no more than once a year. Moves are indeed frequent: families are relocated every two and a half years on average, and every year about 1/3 of all military personnel make a permanent change of station (PCS). In a 20-year career individuals are relocated an average of 12 times.[31] Most soldiers move their families as well: according to the 1987 Survey of Army families, 92% of the responding spouses said they were living in the same location as their spouse; in 1995 in the same survey the percentage was 87.5 (Croan et al, 1992).[32]

[30] In other data the main difference in hospitalization is between infants and others. However, not that age in my sample is observed as of December 31st of the year in question. Therefore many of the children that are 1 years of age and were hospitalized within the last year, may have been infants at the time of the hospitalization.
[31] Source: Relocation Assistance Conference, Dallas 2003.
[32] There are different types of PCS. Training moves are short, lasting about 20 weeks, and families do not move with the soldiers. They are not part of this analysis. Enlisted personnel also move to military bases overseas, also known as OCONUS (outside continental US), for rotation periods of two to three years. Most OCONUS tours are accompanied—soldiers bring their families. Some are unaccompanied and shorter. Unfortunately I do not have pollution data for overseas locations, so families that move abroad leave my sample. Additionally DMDC did not provide data on dependents whose sponsor was stationed overseas. There are also unit moves, which are rare (fewer than 1% of all moves, Rand 1998). Some of these may result in family relocation, if for example a base is closed. They may be related to war activities as well.

In principle the army uses rank and military occupation (MOS) in combination with "needs of the Army" to determine relocation. The military entity that decides on PCSs was previously known as PERSCOM (personnel command).[33] According to Army Regulation 614-200, "the primary goal of the enlisted personnel assignment system is to satisfy the personnel requirements of the Army. Secondary goals are to: a) equalize desirable and undesirable assignments by assigning the most eligible soldier from among those of like MOS and grade; b) equalize hardship of military service; c) assign soldiers so they will have the greatest opportunities for professional development and promotion advancement; and d) meet soldiers' personal desires." This regulation suggests that within rank and occupation (PMOS) all men are treated equally; that within a rank and occupation class, assignment is "random." Relocation is not to be based on prior performance (Lyle, 2003) nor is it systematically associated with promotions (Tarzier 1990).

PERSCOM decides relocations by using an automated system that produces target numbers by MOS, rank, and location, and then constrains assignments to coincide with the targets. Generally, the needs (demand) in a given location within occupation and rank are driven by promotion, end of service, and retirement. Supply is also determined by these, and it is further constrained by regulations governing frequency of moves, training, enlistment, and base-closings, as well as by humanitarian considerations (see below).

Within these constraints, soldiers' preferences may be taken into account. Soldiers submit up to three assignment preferences a few months before their next duty assignment. These choices are not totally unconstrained. The Army suggests that "soldiers should choose installations or geographic areas where their PMOS, SQIs and additional skill identifiers are required". Furthermore "Preference choices must meet the professional development requirement of the soldier's career and a valid requisition must exist that meets the current distribution policy. If both conditions cannot be met, assignments will be made to fulfill Army requirements" (AR 614-200 3.3). (Note that in this study occupation codes PMOS include skill identifiers.) Individuals learn (and the Army

[33] The agency has been renamed and is now called the Human Resources Office.

encourages them, as the regulations suggest) to "play the system." The choices they list take into account the likelihood of being assigned to the location (so it is a constrained choice); it is not clear that location is really chosen even among those assigned their choice. For example, if an individual is due for an overseas transfer, he is unlikely to list a U.S. base in their choices, even if he does not want to go overseas.[34] Below I present evidence from other studies and from my data that indeed individual characteristics do not predict location.

Angrist and Johnson (2000) report that "The nature of duty assignments varies considerably, and families have little control over the timing of moves or the location of the next job," although they do not themselves present evidence to this effect. Several (unfortunately non-representative) surveys conducted by the Department of Defense suggest that, in general, enlisted personnel are not assigned to their preferred location. Hiller (1982), using 1979 survey data, concluded that granting location of choice would be as effective as a bonus of 27% of annual pay in increasing reenlistment.[35] Among those surveyed in 1987, only 35% reported that they were assigned to their preferred location (Burnam et al, 1992). Croan et al. (1992) report that in 1989 about 40% of soldiers did not want to move to the location where they were assigned at the time relocation. Tarzier (1990) reports that "Service Members list constant relocation as one of the major reasons for separating from the Service." This evidence is consistent with the idea that individuals have very little choice over their relocations.

Regulations and available evidence suggest that once an individual has received orders to relocate, it is very difficult and highly unlikely that the decision be overturned. Disobeying relocation orders results in court martial. However, interviews with military personnel revealed that in reality some individuals may have more control over their relocations than others, *prior* to their receipt of relocation orders. For example,

[34] Military personnel suggest that the likelihood that enlisted personnel be relocated to a place of their choice has increased. There are various reasons for this. One is the increased use of computer systems that improve the matches between soldiers' preferences and army needs. Soldiers have access to better information about various bases and now can update their location preferences as frequently as they like online. The army has made efforts to improve retention (re-enlistment rates); respecting location choices has been one of their instruments. Finally, the Army recently moved from an individual replacement system to a unit base system—the new system attempts to keep units intact for at least three years. I thank Robert DeLarouge in the Army's Human Resource Office for providing these details.

[35] Quoted in Vernez and Zellman (1987).

relocations that occur at the time of re-enlistment may be negotiated.[36] According to Croan et al., junior ranking soldiers have the least control over where and when they move. Segal (1986) also suggests that those early in their military career (which is often correlated with but is not the same as rank) have the least control over where and when they move.[37] Because of this evidence the sample is restricted to enlisted personnel (I drop officers). Below, I formally test whether characteristics other than occupation (including skill) and rank predict relocations.[38]

One important issue for this paper is whether relocations are correlated with family health. A relevant point is that the army to some extent does consider family health needs in relocation assignments through the Exceptional Family Member Program (EFMP).[39] Soldiers enroll through their local Army MTF. The EFMP program is designed to be an assignment consideration, if pre-enrolled, and not an assignment limitation. Soldiers could be reassigned to an "all others tour" to meet Army requirements.[40] EFMP only results in reassignments to locations where needs can be met, not to relocations that soldiers prefer. In fact the Air Force advises that "It is very important to remember that the EFMP is not a base of preference program". Anecdotal evidence also suggests that this type of consideration is rarely granted. Furthermore, the Army frequently rejects EFMP applications.[41] For the purpose of this paper it is worth noting that EFMP is not granted because of "Climatic conditions or a geographical area adversely affecting a

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[36] Although there is no information on how frequently this occurs, it may have become a more frequent practice in recent years since re-enlistment rates have been dropping, and personnel retention has become a priority in the army.

[37] Among those interviewed, there was no consensus on this issue: some believed that higher ranking officers had more influence, whereas others suggested that officers, due to their relative scarcity, but also because of expectations about their behavior, had less influence on their relocation. According to Rand (1998) officers experience almost twice as many operational moves as enlisted personnel. This may suggest they are more frequently relocated to undesirable locations.

[38] Similarly Lyle (2003) found (using IV approach) that parental absences appear to be orthogonal to factors determining children's academic attainment.

[39] According to Army regulation AR 614-200, EFMP "allows U.S. Total Army Personnel Command (PERSCOM) to consider the special education and medical needs of exceptional family members during the assignment process and reassign soldiers, when readiness does not require a specific assignment to an area where the needs can be accommodated."

[40] Governing regulation AR 608-75, dated May 1996.

[41] There were 6 major Medical Centers during this period in the Continental U.S. : Dwight D. Eisenhower Army Medical Center (Fort Gordon, Georgia), Womack Army Medical Center (Fort Bragg, North Carolina), Brooke Army Medical Center (Fort Sam Houston, Texas), Madigan Army Medical Center (Tacoma, WA), William Beaumont Army Medical Center (El Paso, Texas), and Walter Reed Army Medical Center (Washington, DC). I could restrict the sample to families in these locations since the health needs of family members would be considered as satisfied for enlisted personnel with access to major medical centers. Unfortunately this would severely limit my estimation sample.

family member's health, [even if] the problem is of a recurring nature."[42] Below I look specifically at whether children's health measures predict location.

I provide statistical evidence that individual characteristics observed at the time of relocation are uncorrelated to base of relocation. Using the sample of individuals that are observed moving in two consecutive years, I estimate N equations of the form:

$$P(location = j)_{i,t+1} = c + X_{i,t}\beta + \sum \gamma_i * I(rank * occupation * year)_{i,t} + \varepsilon_{i,t}, \forall j = 1,...N \quad (1)$$

These are linear probability models that predict the location of individual *i* in year *t+1* based on individual characteristics *X* (which include all of the sponsor's characteristics, mother's hospitalization variables and, importantly, all of the child's hospitalization variables) and a set of dummies for each rank, occupation and year cell.[43] The error terms are clustered at the sponsor level since a sponsor can have several children and they may be observed in more than one year. There are as many equations as bases to which individuals are relocated. Conditional on rank and occupation, the Army claims relocation is "random". Thus, aside from rank and occupation, among those who move between *t* and *t+1*, no other observed characteristics of enlisted men in year t should predict their location in year *t+1*. For each regression, I perform a joint test that β=0. If relocation is random, then the vast majority of the tests should not reject the null.

In Table 2a, I present the distribution of the p-values for these tests. First I look at relocations to all bases (excluding foreign bases[44]) from all bases for parents of children ages 1 to 5.[45] Only in 6.6% of the regressions are individual characteristics predictive of relocation. Thus, at the 10% level we cannot reject the hypothesis that relocations are uncorrelated with observable characteristics beyond occupation and rank. Then I restrict

[42] This information is published online by the Air Force Personnel Center and is available at: http://www.afpc.randolph.af.mil/efmp-humi/efmp-humi.htm. Although this paper looks at Army, not Air Force personnel, this information is indicative of Army practices in general.
[43] The Army suggests that all are treated equally within PMOS and rank groups. I interact these with year since there is no reason to believe that these groups are treated equally over time. Deployments to the Gulf War and relocations due to base closures during this period make it highly unlikely that this is the case.
[44] Recall that the data I obtained did not include information on most personnel stationed overseas.
[45] For this test in order to maximize the sample size I do not drop individuals without access to MTFs or those in bases far from pollution monitors.

my attention to relocations to the bases used in this study. Again, at the 5% level we cannot reject the hypotheses that relocations were quasi-random.[46]

This evidence suggests that for the vast majority of enlisted personnel, relocations are not chosen. A weaker, but relevant test for this study, is to look at whether personal characteristics predict pollution at relocation bases. Note that desirable bases in terms of relocation need not be low pollution bases. In interviews, bases located closer to cities were generally preferred, and they tend to be more polluted on average. Some bases are universally thought of as undesirable locations, mostly for their remoteness and weather conditions, and due to the lack of availability of some services such as good schools. On the other hand, these same rural bases can be desirable from a career perspective because of the training opportunities available. (Fort Polk is a frequently cited example.) Overall there is no unambiguous way in which individual characteristics would be related to pollution levels at the base, even if individuals were able choose their location. To test this in the data I estimate the following equations:

$$Y_{i,t+1} = c + X_{i,t}\beta + \sum \gamma_i * I(rank * occupation * year)_{i,t} + \varepsilon_{i,t}, \quad (2)$$

where Y is the pollution level that individual i is exposed to in year *t+1*, and *X* includes all of the same individual characteristics mentioned above, including year *t*'s hospitalization variables for mother and child. I estimate one equation per pollutant. Again the sample is restricted to those that move between two years. The errors are clustered at the sponsor level. For each equation I test whether the *X*s are jointly significant. The results are presented in Table 2b. In all cases, the test does not reject the null that the *X*s are not significant. In the bottom of the table I re-estimate the equations year by year. In only 3 out of 35 equations do we reject the null, suggesting that indeed individual characteristics do not predict pollution exposure.

In spite of this evidence I collected additional data to assess whether choice of location affects the results. I calculated the distance from each installation to the closest city (for

[46] Ideally one would allow for the error term to be correlated across equations, but it was not possible to estimate all equations at once for technical reasons. STATA will not estimate SUR with a large number of equations.

various city sizes) and also obtained aggregate statistics on the frequency with which bases are listed as individuals' top choices for 1991 to 1995 from West Point. These measures can be used as proxies for unpopularity in the regressions, or alternatively they can be used to restrict the estimation sample.

IV. Main results

A. Empirical approach

For each age group (ages 0 to 1, and ages 2 to 5), I estimate the following individual level linear probability model,[47]

$$Hosp_{ibt} = c + P_{ibt}\mu + X_{ibt}\beta + Z_{bt}\delta + \sum \gamma * I(rank * occupation * year)_{ibt} + \varepsilon_{ibt}, \quad (3)$$

where the dependent variable *Hosp* is a dummy variable indicating whether or not the child was hospitalized during the year for a respiratory condition; *X* is a matrix that includes age, race and gender of the child, and *γs* are the coefficients for each possible rank*occupation*year cell. Z is a matrix of base-level characteristics. Because weather is a potential confounder, rain, temperature and temperature-squared are included in all models; some models include additional base controls. The coefficients of interest are the estimated *μs*, which represent the effect of a given pollutant *P* on the probability the child was hospitalized during the year. The errors are clustered at the base level to account for the fact that all individuals in the same base are exposed to the same levels of pollution, and these levels are likely to be correlated over time within base (Bertrand et al, 2004).[48]

In this baseline regression, estimates of the effects of pollutants are identified from cross-sectional variation, by simply comparing the (predicted) hospitalization rates of children in high pollution areas with those in low pollution areas. If location is indeed not chosen

[47] Logit specifications yield very similar results.
[48] In addition the standard errors would need to be corrected because pollution levels are predicted. However this correction is very difficult to implement. There are two reasons I did not attempt to make such a correction here. The first is that the effect of measurement error on the standard errors is likely to be much larger. Secondly, the asymptotic properties of the predictions are based on "infill asymptotics" (Cressie 1993), where the number of pollution monitors increases and fills the space, whereas the asymptotics here are based on increased sample size.

and pollution is uncorrelated to own characteristics, then adding individual characteristics should not affect the estimates. Importantly among individual characteristics I can control for whether the child was hospitalized for an external cause (which mostly include accidents and violence-related episodes). This should capture additional family characteristics.

In principle, one of the advantages of the military is that their lifestyle will remain relatively stable as they move across the country. However there may be characteristics of the location that vary with pollution and also affect health, such as proximity to an urban area. In order to separate the effects of pollutants from those of other base characteristics I take several approaches. One is to control for a number of base- and year-level characteristics such as distance to the closest military treatment facility, distance to the closest city, and other base characteristics that were described in the appendix, including the percentage of sponsors that requested that base that year, and the percentage of children that were hospitalized for external causes. This last variable should control for other base characteristics like crime. Lead is also included as a base level control, although the predictions for lead are fairly poor. Alternatively, I estimate equation 3 using base fixed effects to control for site-specific characteristics that are time invariant. In these regressions, identification comes from changes in pollution overtime within bases.

B. Main results

The results from estimating equation 3 for each age group are presented in table 4. The first column shows the effects of pollution when only age, gender, race and weather (temperature and rain) are included (in addition to rank*occupation*year dummies). The results for ages 0 to 1 show a significant negative effect of SO_2 on hospitalizations, a significant positive effect of NO_2 and no significant effects for PM10, CO or O_3. The pattern is different for children ages 2 to 5. For them there appears to be a significant positive effect of O_3 and a negative effect of PM10, whereas all other coefficients are insignificant.

Column 2 adds all parental controls and a dummy for whether the child was hospitalized for an external cause. The sample sizes fall somewhat because some individuals are missing some of the parental characteristics, so the last column of the table presents the results with the smaller sample and only basic controls. In all three regressions the estimated coefficients are very similar, especially for children ages 2 to 5. This is consistent with previous results that individual characteristics are uncorrelated with pollution levels at the base.

Next I examine the effect of base-level controls. Column 3 adds all base characteristics, and column 4 uses base fixed-effects. In column 5 I add parental characteristics and base characteristics, and finally column 7 adds all possible controls. The results from adding base characteristics and/or base fixed-effects suggest that the basic results for children ages 0 to 1 are not robust: when these additional controls are added SO_2 becomes positive and insignificant and NO_2 also becomes insignificant. In fact in these regressions no pollutant has a significant effect on hospitalizations. Moreover the test for the joint significance of all pollutants does not reject the null at the 5 or 10% level (see results in Table 6 explained below). However the sample of children ages 0 to 1 is small.

On the other hand the results for children ages 2 to 5 are different. In all specifications, the effect of O_3 is positive and significant (although it is somewhat bigger once base characteristics or fixed effects are added). The negative and significant effect of PM10 disappears with the addition of base fixed-effects. All other coefficients remain insignificant (although CO is significant at the 10% level in column 4).

In the last column, as a final way to assess whether omitted individual- and base-level characteristics are driving the results, I look at whether pollution predicts the probability that a child will be hospitalized for an external cause. For children in both age groups, all of the coefficients for individual pollutants are statistically insignificant. Neither are they jointly significant.[49]

[49] The p-values for the children ages 0 to 1 and 2 to 5 are 0.9724 and 0.6350 respectively.

The results from this table suggest that there are no statistically significant effects of pollution for children ages 0 to 1 on respiratory hospitalizations, and that O_3, but no other pollutant, significantly increases the probability of a respiratory hospitalization for children ages 2 to 5. In terms of magnitude the coefficient on O_3, which ranges from 0.163 to 0.27, implies that an increase of one standard deviation in O_3 (0.008) increases the probability of a respiratory hospitalization by 0.0013-0.00216 percentage points, or about 10-17%, relative to the mean for children ages 2-5 (0.0124). The implied elasticity ranges from 0.7 to 1.14, which is fairly large.

C. Specification checks and other estimation issues

Table 5 shows a number of additional specification checks done to gauge the robustness of the results. The first column reproduces the results with just the basic controls. In column 2 I add dummies for whether the closest monitor for a given pollutant is more than 30 miles away. In column 3 pollution variables are interacted with these dummies (so the coefficients show the effect of pollution if the monitor is within 30 miles—interactions are not shown). What these results suggest is that it is the distance to the monitor that is responsible for the differences in the estimated coefficients when adding base characteristics or fixed effects. Note that the coefficient on SO_2 switches sign and the coefficient on NO_2 becomes insignificant. Also these distance-to-monitor controls increase the coefficient of O_3, and it remains at that level when we add additional base characteristics (column 4) for the older children. These results are important in that they suggest that base characteristics do not affect the results, but also that distance to the monitors does. This suggests that measurement error in pollution predictions is important. Interestingly, the results for children ages 0 to 1 suggest that this measurement error is not random, since it does not always result in attenuated coefficients. I explore this issue below.[50]

[50] In their literature review, Dominici et al (2003) identify the modeling of measurement error as an area in need of further research.

Columns 5 through 11 re-estimate the model with all controls, dropping one year at a time. Recall that years 1990 and 1991 could be problematic because of deployments to the first Gulf War. Also 1995 is of concern because it is missing ¼ of that years' hospitalizations, and because of the shift from Champus to Tricare. Nonetheless, the results are very consistent. In none of the specifications are the effects of pollution significant for ages 0 to 1, whereas the effect of O_3 is always positive and significant for children ages 2 to 5 (except for the regression that drops 1989, but note that the point estimate in this regression is quite similar to that of other regressions).

In columns 12 and 13, I test the sensitivity of the results to pollution outliers in the data. In column 12 I drop observations where the value of any pollutant exceeds its 99th percentile or is below its 1st percentile. This restriction has very little impact on the results. However, Figure 6 suggests that higher values rather than lower values of pollution may be problematic. The last column drops all observations where the value of the pollutant exceeds its 90th percentile for every pollutant. The results for younger children are unchanged. For children ages 2 to 5, the effect of O_3 increases in magnitude (it is not significant but the sample size has fallen), and interestingly the effect of CO increases and becomes marginally significant. Overall the results from table 5 suggest that the estimates are robust to a variety of specification checks.

To further explore measurement error in the predictions, Table 6 compares the results obtained from different predictions methods, and from limiting the sample based on distance to monitor. I do so using the basic model that controls only for gender, race, age and weather (in addition to pmos*rank*year dummies). The first column reproduces the results using the basic specification. In the next column instead of adding all pollutants at once, I enter them one at a time. Because pollutants are correlated, and they can all potentially affect health, single-pollutant models (which are the most commonly used in the literature) can generate biased estimates of the effects of the pollutant in question. For both age-groups, the results are different and mostly insignificant, although the effect of O_3 remains significant for children ages 2 to 5.

Next I compare Kriging to deterministic predictions (IDW), although it is clear that from a theoretical perspective Kriging estimates are to be preferred. In the next two columns I present the results that compare IDW30 and Kriging using the same estimation sample (i.e. limiting the sample to only those with monitors for all pollutants within 30 miles). For children ages 0 to 1 once again we see that limiting the sample based on distance to monitor reverses the coefficient on SO_2 and on NO_2. For children ages 2 to 5 the coefficient on O_3 becomes larger. Interestingly, although insignificant, the coefficients on SO_2 and on NO_2 also switch sign in the older sample once I make the distance restrictions. Overall it would appear that these two pollutants have a significant amount of non-random measurement error. Otherwise Kriging and IDW30 yield coefficients of about the same magnitude for those coefficients that are significant, although the standard errors are quite different. In the next two columns, I compare IDW15 and Kriging. In these specifications the size and sign of the coefficients is quite different although it is worth noting that no coefficient is significant (although the sample is now quite small), except that CO is positive and significant for the older children.

Lastly I compare Kriging to county-weighted average predictions. The rationale for these predictions is not based on spatial correlation, but rather by the idea that county averages may be a better measure of exposure than (precise) measures of ambient levels of pollution. Although it is well known that ambient levels are not necessarily good predictors of exposure, it is also not clear (and not known) that county average are better proxies for exposure. So it is difficult to determine which set of estimates is best. These two methods produce very different coefficients, although again most coefficients are insignificant, so unfortunately it is difficult to draw conclusions.

In summary this section has shown that O_3 has a robust positive and significant effect on the probability that a child age 2 to 5 is hospitalized for a respiratory condition during the year. There are no significant and robust effects of pollutants for younger children. NO_2 and SO_2 are very sensitive in both samples to distance from monitors and produce results that are unstable in both magnitude and sign. In some specifications CO is sometimes positive and significant for older children, but the magnitude of CO estimates (and their standard error) also appears to be sensitive to distance to monitors and to outliers.

V. Additional results

A. Exploring the Functional Form

All the models above are linear functions of different pollutants. However it is possible the effects of pollution are non-linear. The EPA uses certain cutoffs as thresholds beyond which pollution levels are classified as dangerous or very dangerous. (See Appendix B.) However there is little scientific evidence for threshold effects; little is known about the shape of these relationships generally. Additionally it has been suggested that the deleterious health effects of some pollutants can be exacerbated (or diminished) by the presence of other pollutants (i.e. there may be more than additive effects).[51] This suggests that models with interactions between pollutants may be more appropriate. This discussion suggests that it is necessary to explore the functional form of the equation of interest.

There is no a-priori consensus on how to choose the variables that should be used in a regression, in particular higher order terms. The number of higher order terms for example has to be chosen somewhat arbitrarily. Additionally the statistical properties of models that include terms using pre-testing are not known. Finally in the context of this study, there are two additional caveats. Non-linear models will be sensitive to outliers which are common for all pollutants examined here. Also these models require more variation in pollution since they must identify effects in different regions of support. This study uses 940 base*year observations to identify the effect of pollutants (since everyone in a given base and year is subject to the same pollution levels). As we add interactions and higher order terms the identification becomes less precise.

[51] For example PM is suspected to interact with almost all pollutants, in particular O_3, and SO_2, because O_3 and SO_2 can inflame the lungs, increasing the rate at which PM is absorbed. There are some controlled studies that examine the effects of two-pollutant mixtures in humans and animals; these studies suggest there exist more than additive effects, for example between PM and O_3 (WHO 2003). The EPA (1996) reported that "This issue of exposure to copollutants remains poorly understood, especially with regard to potential chronic effects."

In Table 7 I investigate whether the data suggest interactions and higher order terms belong in the model. I do so using the model that includes all possible controls (all individual and parental characteristics, all base characteristics and base fixed-effects). As is commonly done, I arbitrarily choose to start by including up to five level higher order terms (x, x^2…x^5) and up to five level interactions (or combinations of pollution; the fifth level interaction is PM*CO*NO_2*SO_2*O3) and drop the highest order terms progressively.[52] For each model I report three measures of fit, the adjusted r-squared, the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC). I also report the p-value for the test of joint significance of all pollution terms, of all interactions, and higher order terms (excluding the main linear terms) and for the higher order terms. Because the results may be sensitive to outliers, I report these results with the entire sample, and also for a sub-sample that excludes all observations where pollution exceeded the 90th percentile for each pollutants respectively.

In all of the specifications tested and for both age groups, the models always reject the null that the higher order interactions/terms are jointly 0, regardless of which terms are included. Additionally, the measures of fit suggest that the models with higher order terms and/or interactions are a better fit. Although these non-linear models are sensitive to the inclusion of covariates (in particular the magnitudes of the coefficients is quite different without all the controls[53]), these conclusions are not: the models with higher order terms and interactions are better fits, and these terms appear to be jointly significant in models that include only basic controls.

These models are difficult to interpret. In figures 7a and 7b I report the implied marginal effects for each pollutant from models that include all the possible terms, since this is the preferred specification when outliers are excluded. For children ages 2 to 5, with or without outliers, these graphs suggest that the marginal effects of CO, PM10, and O_3 are relatively constant, whereas the effects of NO_2 and SO_2 appear to be increasing. However

[52] Ideally one would estimate 2^{50} models (there are 50 possible terms one can include in the regression) and choose the model with the highest fit. Instead I present specifications that include all terms, interactions only, or high-order terms only.
[53] Results not shown, available upon request.

the standard errors (not shown) are very large. For children ages 0 to 1, the conclusions are similar, although again it is worth noting that for this group the results are much more unstable, most likely because of the smaller sample sizes.

Unfortunately, because of the limited variation in the data and the fact that the variation of pollution levels is not independent from one pollutant to another, these models are limited in their ability to identify the true underlying shape of the relationships. However the data strongly suggest that non-linearities and interactions are important. This is an important topic for further research.

B. Some issues in interpreting the results

In the previous sections the effects of pollutants were interpreted by thinking of the estimated coefficient as the partial effect of increasing one pollutant while holding all other variables constant. However this standard interpretation may not be appropriate here for two reasons.[54] First, although individual exposure to a particular combination of pollutants may be "random", exposure to a single pollutant is not. Second, it may not be physically possible to lower one pollutant while "holding all others constant": some combinations of pollution may not be physically attainable. This is because of the way pollutants interact with each other. NO_2 and SO_2 are precursors of PM10 and O_3. So reductions in NO_2 or SO_2 may lower PM10 levels as well. However these interactions are complex. For example it is well known that there is an O_3-NO_2 cycle. Lin (2004) shows that emissions of NO_2 can either increase or decrease the levels of O_3, depending on other conditions at the location. Furthermore O_3 can degenerate into NO_2. This simplified example illustrates that it may not be sensible to think of partial effects in our model given that these cross-pollutant effects are not known. This is particularly relevant for policy exercises since the partial effect will not answer the most basic policy question, namely what the effect is of lowering emissions of a particular pollutant.[55] It also

[54] This problem is noted for example by Dominici et al (2003). This issue is usually ignored in many studies.
[55] To obtain appropriate estimates of the effects on health of policies that regulated single pollutants, it is necessary to combine the estimates obtained here, with estimates of how the distribution of all pollutants changes when emissions of one pollutant are decreased at particular locations. This type of estimation is beyond the scope of this paper and necessitates additional information not available to me at this point. See Dominici et al (2003) for a discussion.

suggests a reason why some of the estimated coefficients (here and in other studies) can sometimes be negative.

An alternative way to interpret results from these multi-pollutant models is to think of feasible policy interventions. The one I consider here is to compare the predicted percentage hospitalized for respiratory conditions across locations with very low and very high levels of pollution for all pollutants, while holding other variables constant (I set them equal to the sample mean). This is akin to moving individuals from high to low pollution areas, or comparable to reductions over time of all pollutants. This experiment lowers all levels of pollution simultaneously to combinations that are feasible (since they are observed).

Table 8 presents these results for children ages 2 to 5 (since pollution appears not to be significant for the younger children). Panel A shows the results of the experiment using the linear model. The actual (and predicted) percentage of children hospitalized for respiratory conditions is 1.15%. However the percentage is higher (1.4) for those living in bases where all pollutants are high (all above their 70th percentile) and lower (0.7) where all are low (all below their 30th percentile).

In order to assess how much of this difference is due to differences in pollution levels rather than in other characteristics, I compare the predicted percentages, holding all other variables at their mean. In models that include only basic controls, the difference between the two groups is 0.0009, so that moving from a high to a low pollution area lowers predicted hospitalization by about 8%. If I include all controls, then the difference increases to 0.0138, so that the same move from high to low pollution areas reduces the percentage hospitalized by 77%. The predictions using the non-linear fully interacted model (dropping outliers[56]) are presented in Panel B. When using only basic controls, moving from a high to a low pollution area lowers the percentage hospitalized by 40%. When all controls are included the decline is again about 77%. Overall these are very

[56] The results using the full sample are similar when adding all controls, but they are quite different when only the basic controls are included. As mentioned in the section above, these results are sensitive to the inclusion of controls, especially when the outliers are included. Given the number for base*year pollution observations, this is not surprising. Results available upon request.

large decreases, but the pollution changes that are being considered are also quite large. This experiment suggests that pollution levels have large effects on children's respiratory disease, especially since hospitalizations are an infrequent and extreme manifestation of such diseases.

C. Heterogeneous treatments effects

Evidence from other studies suggests that the effects of PM10 are larger for individuals with low SES (education and income). There appears to be no such effect for O_3 or NO_2, except that the impact of O_3 and NO_2 appear to be larger for (already) asthmatic children. However these estimates are possibly biased because of the non-random exposure to pollution across SES groups. On the other hand it is possible that the effects of pollutants differ across SES groups since there may be genetic differences by gender or race. These groups may be exposed to different levels of pollution (there appear to be non-linearities) and they may have different behaviors that may exacerbate the effect of pollution (e.g. smoking or differential outdoors exposure).

In order to look at this question I estimate models again stratifying by race, education and rank. These results are presented in Table 8 for the older children. (I do not present results for children ages 0 to 1 since these results are not robust and mostly insignificant.) Rather than interacting pollution with SES, I stratify by SES because I reject the null that the coefficients on all variables and on non-pollution variables are the same for all groups. (The p-values for these tests are reported in the table.)

Panel A shows the results from estimating the basic model. I find no differences between blacks and whites in the effect of O_3, CO and PM10. On the other hand effect of O_3 appears to be significantly higher for children of more educated parents and for children of higher rank. I ignore the results for NO_2 and SO_2 since these results are unstable. When adding all possible controls (Panel B), I find that none of the coefficients are statistically different by race or education (but the sub-sample of children of educated fathers is quite small). However the effect of O_3 still appears to be higher for those of higher rank.

These results are somewhat unintuitive since previous research suggests higher effects for low SES individuals. However, recall that in this study there are no differences in the pollution levels that high and low SES families are exposed to; these families live in very similar environments and they all have access to (almost free) health care. The only reason why we might still expect differences by SES are related to families' behaviors at home.

Why would the effect of O_3 be higher for higher SES children? The EPA suggests that "several groups are particularly sensitive to ozone—especially when they are active outdoors—because physical activity causes people to breathe faster and more deeply. Active children are the group at the highest risk from ozone exposure because they often spend a large fraction of the summer playing outdoors."[57] Previous research documents that high SES children are more likely to be physically active (Gordon et al 2000, Andersen et al, 1998). In particular in a study of military and civilian children, children of officers were found to be more physically fit and to watch fewer hours of television compared to children of enlisted personnel (Stephens et al 2003). If indeed higher SES children spend more time outdoors, this would explain why the effects of O_3 are larger for them (recall that indoor levels of O_3 are not highly correlated with outdoors levels). Outdoor exposure may also explain why there are no significant effects of O_3 for children ages 0 to 1, since they are much less likely to play and exercise outdoors.

VIII. Conclusion and discussion

This study uses plausibly exogenous variation in pollution induced by military relocations to identify the effect of the 5 major air pollutants on children's respiratory hospitalizations. I find that for military children ages 2 to 5, only ozone (O_3) appears to have an adverse effect on health, measured by respiratory hospitalizations. These effects

[57] EPA online brochure "Ozone and your health," available online at http://www.epa.gov/airnow/ozone-bw.pdf

are large: the implied elasticity for the probability that a child is hospitalized for a respiratory condition with respect to O_3 is between 0.7 and 1.14. Furthermore I find that the effects of ozone appear to be greater for children of higher SES, consistent with previous findings that children that exercise outdoors are at higher risk for ozone. No other individual pollutant appears to significantly affect respiratory hospitalizations (although there is evidence of complementarities across pollutants). Also I do not find any robust and significant effects for children ages 0 to 1, but this may be due to the fact that the sample is small.

Because it is not clear that partial effects are meaningful in the multi-pollutant models estimated here, I predict the effects of moving from high to low pollution areas. The results suggest the effect of such a move is to reduce the percentage of children ages 2 to 5 hospitalized for respiratory causes by as much as 77%, which again suggests the effects of pollution on respiratory diseases in children are large.

The results in this paper differ somewhat from the results in Chay and Greenstone (2003), who find a significant effect of PM10 on infant mortality (although they do not include any other pollutants); and Currie and Neidell (2005) who find that only CO predicts infant mortality (the effects of PM10 and O_3 were insignificant). Both of these studies look at infant mortality instead of hospitalizations and they have much bigger samples of infants in their analysis compared to the sample of infants available here.

There are a number of additional methodological findings. I used several methods to impute pollution at the zip code level, and test the sensitivity of the models to distance from monitors. This is important because monitors are not randomly located across the country. I find evidence that measurement error in pollution predictions is not random, and that it has large effects on the estimated coefficients. Also, I find that models that look at the effects of one pollutant at a time can be very misleading. Moreover the data strongly suggest that non-linear models, and models that include interactions between pollutants (which are rarely used), are preferable to linear models. However the variation in the data is not sufficient to appropriately identify these relationships. This is an important area for future research.

This study has a few limitations. First the only outcome analyzed is whether an overnight hospitalization occurred. This is a rather extreme outcome, and it is possible that pollutants affect the respiratory system without resulting in overnight hospitalizations. Previous studies have found that there are about 3 emergency room visits for every hospital admission (EPA and HSPH 1995).

Another issue is that pollutant measures are averaged over the year, using measures of ambient pollution. It may be that average pollution levels in the year are not what matters for health but rather, for example, whether pollution frequently exceeds a certain threshold. I experimented with alternative measures, but statistical models to predict percentiles or maximums are not well developed and resulted in very poor predictions (see Cressie 1993).[58] Also, this study uses pollution as measured at non-randomly positioned EPA monitors, and uses those measurements to predict pollution levels across the country. Military bases may have their own sources of air pollution, which may be relatively local and not captured here.

The last issue is whether the results are representative of the effects for the population at large. Only the effects for children are analyzed; not considered here are the effects on the elderly—another high-risk population—nor on adults. Compared to other children, military children are exposed to somewhat lower pollution levels. The demographic characteristics of families in the Army differ from that of the average family: they tend to be younger, poorer, and are less likely to be white. More importantly, military families have benefits that are not common among civilians with the same socio-economic background, including for example generous health insurance.

[58] I estimated models that predicted the percentage of the year that pollution exceeded a certain threshold using indicator Kriging methods. These models had very low measures of fit or could often not be estimated.

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Appendix A: Data Sources and Description

A. Data Sources for pollution

Through a Freedom of Information Act (FOIA) request, I obtain from the EPA yearly statistics at the monitor level for the major 6 pollutants in the US. The latitude and longitude of the monitors is reported, as are annual summary statistics, including the mean and various percentiles of the distribution for that year. As suggested by the EPA I drop exceptional event recordings; also, for PM10, TSP and Pb only daily measurements are used. For all other pollutants, only hourly measurements were used.

In principle, data consists of one observation per monitor per year; for some pollutants/years this is not the case; the EPA said this is because sometimes agencies report measurements using different collection or analysis methods; it is to be expected that there are more observations per monitor per year for TSP, Pb and PM10 because part 58 of federal regulations requires that multiple measures be taken at the same site. Although agencies are not required to report multiple measurements, many do. I kept the measurements that span the longest period of the year, based on quarter information. If there were still multiple measurements by monitor within a year, the average value was used. A complete panel of monitors from 1988 to 1988 was constructed following the EPA guidelines, by keeping only those monitors for which data exist for 8 out of 11 years. The missing values were linearly interpolated.

B. Military data

Through a FOIA request, I obtain individual-level data on enlisted married men in the military and their families from 1988 through 1998. This data was specially created for this project by the DMDC by matching data from multiple sources collected by different branches of the military.

Demographic and employment characteristics of the active-duty members come from the "Active Duty File." The data is collected monthly, DMDC matched only the December files to other information of the dependents (for feasibility reasons).

Demographic information for spouses and children come from the DEERS (Defense Enrollment Eligibility Reporting System) file, some of which is also available in the Active Duty Files.

From 1988 until 1995 the majority of the private insurance claims are from the CHAMPUS (Civilian Health And Medical Program of the Uniformed Services) insurance files. Champus was replaced by a new insurance system in 1995, so claims filed after this date come from the Tricare insurance files. (There were demonstrations in Hawaii and California from 1988 to 1994, but Tricare was officially implemented in 1995, although it was phased in at different rates regionally.) These data (Champus and Tricare) contain claims for both hospitalizations and for all other types of claims.

For hospitalizations that occurred at military facilities, the claims come from a file labeled the “Biometrics file,” a record from the military treatment facilities. They only exist for hospitalizations.

All these files were merged within year and across years using Social security number of enlisted men. A scrambled version of this unique identifier is provided in the final data.

West Point provided me with the following additional data:

1. Annual data from 1991 to 1995 on the number of first-requests for relocation made by Army personnel, aggregated to the level of the requests. Requests are made either for states, for military installations, or more precisely for specific posts within each individual installation.
2. A list of all military treatment facilities (MTFs) and Major Medical Centers in existence between 1991 and 1995, along with their zip codes.
3. A list of all the zip codes and ARLOCs where enlisted personnel reported being on duty after 1991. This list was used to match all duty zip codes in the data provided by DMDC with a unique ARLOC number, i.e. a military installation. Large military installations can contain more than one zip code, but each zip code was associated with a unique installation. Unfortunately West Point did not have readily available a cross walk between duty zip code and ARLOCs, which explains why it was necessary to use enlisted personnel reports to derive it.

C. Weather data

Wind data were provided by the National Climatic Data Center. Annual averages for all years in the 1930-1996 period are reported in the document “Climatic Wind Data for the United States,” which is available online at http://www.ncdc.noaa.gov. The document reports wind direction and speed.

Annual means for temperature and precipitation come from the “United States Historical Climatology Network (HCN) Serial Temperature and Precipitation Data” provided by the National Oceanic and Atmospheric Administration of the National Climatic Data Center. The data is available online at ftp://ftp.ncdc.noaa.gov/pub/data/ushcn/.

D. Additional data

Distance to cities of various sizes was calculated using data provided with ARCGIS software.

Appendix B: Background information on the 6 major air pollutants

Air Pollutant	Largest source[1]	Other sources[1]	Recommended threshold for annual arithmetic mean (2000)[2]	Air Quality Index thresholds [3]	Suspected Health effects[1]
Lead Pb	Metal processing (52%)	Fuel combustion, waste disposal	1.5 ug/m^3 QUARTERLY AVERAGE	N/A	Children: seizures, mental retardation, learning deficits Long term: (in adults) high blood pressure, hypertension, heart disease
Sulfure Dioxide SO_2	Electric Utilities (67%)	Industrial fuel combustion (coal and oil)	0.03 ppm 80 ug/m^3	Good: 0.001-0.034 Moderate: 0.035-0.144 Unhealthy for some: 0.145-0.224 Unhealthy: 0.225-0.304 Very unhealthy: 0.305-0.604 Hazardous: 0.605+	Short term: Aggravation of asthma in children. Long term: Respiratory illnesses and aggravation of cardiovascular disease Outdoor exercise worsens effects
Ground Level Ozone O_3	NO_x and VOC are precursors of O_3. Motor vehicle, electric ulitities and industrial emissions are sources for NO_x and VOC.	Gasoline vapors, and chemical solvents	0.08 ppm 157 ug/m^3 8 HOUR AVERAGE	Good: 0-0.064 Moderate: 0.065-0.084 Unhealthy for some: 0.085-0.104 Unhealthy: 0.105-0.124 Very unhealthy: 0.125-0.374 Hazardous: Not specified	Short term (up to 8 hours exposure): Aggravation of asthma in children Respiratory infection, lung inflammation. Especially with outdoor activity. Long term (repeated exposure): chronic respiratory diseases. Cardiovascular disease and other symptoms (head cold, sore throat).
Nitrogen Dioxide NO_2	Motor vehicles (49%)	Utilities; industrial, commercial and residential fuel combustion.	0.053 ppm 100 ug/m^3	Good: Not specified Moderate: Not specified Unhealthy for some: Not specified Unhealthy: Not specified Very unhealthy: 0.650-1.240 Hazardous: 12.50+	Short term (up to 3 hours exposure): aggravation of pre-existing respiratory illness/asthma, increases in upper respiratory illnesses in children ages 5-12 Long term: respiratory infections, heart failure and ischemic heart disease

Appendix B Continued

Air Pollutant	Largest source	Other sources	Recommended threshold for annual arithmetic mean (2000)	Air Quality Index thresholds	Health effects
PM10	Directly emitted into the air: motor vehicles, factories, construction, tilled fields, unpaved roads, stone crushing, wood burning.	Indirect production: gases from burning fuels react with sunlight and water vapor. SO_2 and NO_2 and precursors of PM10.	50 ug/m^3	Good: 1-54 ug/m3 Moderate: 55-154 Unhealthy for some: 155-254 Unhealthy: 255-354 Very unhealthy: 355-424 Hazardous: 425+	Aggravated respiratory conditions, such as asthma; children and elderly most at risk Long term: lung cancer, cardiovascular problems in adults.
Carbon Monoxide CO	Motor vehicles (56%)	non-road engines and vehicles, industrial processes Indoors: Woodstoves, gas stoves, cigarette smoke, and unvented gas and kerosene space heaters	9 ppm 10 ug/m^3 8 HOUR AVERAGE	Good: 0.1-4.4 ppm Moderate: 4.5-9.4 Unhealthy for some: 9.5-12.4 Unhealthy: 12.5-15.4 Very unhealthy: 15.5-30.4 Hazardous: 30.5+	Low levels of exposure: aggravated cardiovascular disease, angina pectoris. High levels: visual impairment, learning disabilities. low birth weight, disabilities, mobility disabilities, cardiovascular disease (heart failure)

(1) Sources: Ozone http://www.epa.gov/oar/oaqps/gooduphigh/ozone.html#6, (2) Source: (3) Source: http://www.epa.gov/airnow/aqi/aqi_conc_calc.html

Appendix C: Models of spatial correlation—review

This section draws heavily on Cressie (1993). Kriging is a statistical method that estimates a model of spatial correlation and uses that model to generate predictions. Statistical models of spatial correlation are closely related to time-series models used in economics. The main difference is that in time series models there is only one dimension (time) across which observations are allowed to be correlated. Models of spatial correlation allow values to be correlated in space. Kriging estimation is akin to Feasible Generalized Least Squares Estimation. It consists of estimating the parameters that describe the serial correlation between observations (like estimating ρ for an AR(1) model—or more generally estimating the variance covariance matrix) and then of using the estimates to find the predictions that minimize the sum of squared errors. Although the principles of correlation and estimation are similar, there are difficulties that arise in spatial correlation models due to the increased dimensionality of the problem.

Kriging

The model for ordinary Kriging is

$$Z(s) = \mu + \varepsilon(s)$$

where $s = (x, y)$ is a location, and x and y are the coordinates of that location in space; $Z(s)$ is the value associated for that location. The pollution data that the EPA collects is of this form; longitude and latitude (x and y) of each monitor are known, as well as the pollution level Z at that location. The error term $\varepsilon(s)$ are random errors with spatial correlation that follow a normal stationary process. Finally μ is a constant term—the data is assumed to exhibit no trend. Kriging finds the best linear unbiased predictor for a given location that minimizes the mean squared error. Therefore the Kriging estimator at a particular location s_0 is found as follows:

$$\min_{\lambda_1 \ldots \lambda_n} E\left(z(s_0) - \sum \lambda_i z(s_i)\right)^2 s.t. \sum \lambda_i = 1$$

$$where$$

$$z(\hat{s}_0) = \sum \lambda_i z(s_i)$$

Thus the prediction for the value at a given point s_0 is a weighted average of values within a certain distance of s_0. The weights λ_i are unknown. They are constrained to sum to one to guarantee the predictions are unbiased. Further define the semi-variogram of the model as given by

$$\begin{aligned} 2\gamma(h) &= \operatorname{var}(z(s+h) - z(s)) \\ &= E\left(z(s+h) - z(s)\right)^2 \end{aligned},$$

where h is the distance between i and j, and the second equality holds because under the assumption of stationarity $E(z(s+h) - z(s)) = 0$. Another way to write the semi-variogram between locations s_i and s_j is

$$2\gamma(s_i - s_j) = \text{var}(Z(s_i) - Z(s_j))$$
$$= E\left(Z(s_i) - Z(s_j)\right)^2$$

The Lagrangian for this minimization is given by:

$$L = E\left(Z(s_0) - \sum \lambda_i Z(s_i)\right)^2 - 2m\left(\sum \lambda_i - 1\right)$$
$$= E\left\{-\frac{1}{2}\sum_i \sum_j \lambda_i \lambda_j \left(Z(s_i) - Z(s_j)\right)^2\right\} + 2E\left\{\frac{1}{2}\sum_i \lambda_i \left(Z(s_0) - Z(s_i)\right)\right\} - 2m\left(\sum \lambda_i - 1\right)$$
$$= -\sum_i \sum_j \lambda_i \lambda_j \gamma(s_i - s_j) + 2\sum_i \gamma(s_0 - s_i) - 2m\left(\sum \lambda_i - 1\right)$$

where *m* is the Lagrange multiplier associated with the constraint. The first transformation is obtained by transforming the expectation using the constraint. Taking derivatives with respect to λ and m we obtain $(n+1)$ equations:

$$\frac{\partial L}{\partial \lambda_i} = -\sum_j \lambda_j \gamma(s_i - s_j) + 2\gamma(s_0 - s_i) - m = 0, \forall i$$
$$\frac{\partial L}{\partial m} = \sum \lambda_i - 1 = 0$$

This is a constrained linear optimization problem, which can be more generally re-written as:

$$\begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1N} & 1 \\ & & & \\ \gamma_{N1} & \cdots & \gamma_{NN} & 1 \\ 1 & & 1 & 0 \end{bmatrix} * \begin{bmatrix} \lambda_1 \\ \\ \lambda_N \\ m \end{bmatrix} = \begin{pmatrix} \gamma_{10} \\ \\ \gamma_{N0} \\ 1 \end{pmatrix}$$

The weights are the unknowns, as well as the parameter *m*. The values of the matrices γ_{ij} are the semi-variogram between two points, and they are equal to ½ of the variance between the value at *i* and all values at distance *j*. The solution for this problem is given by

$$\hat{\lambda} = \Gamma^{-1} g$$

In order to construct the weights we need estimates of γ_{ij}. These are estimated using a parametric model of serial correlation. Below are the models that were used in this paper, the spherical and the exponential being the most commonly used.

Co-Kriging

The model for co-Kriging is

$$Z_s = X_s\beta + \varepsilon_s$$

The error term ε_s are random errors with spatial correlation that follow a normal stationary process, N(0, Σ). The GLS estimator of β is given by:

$$\hat{\beta} = \left(X'\Sigma^{-1}X\right)^{-1} X'\Sigma^{-1}Z$$

$$COV(\hat{\beta}) = \left(X'\Sigma^{-1}X\right)^{-1}$$

Parametric models of spatial correlation: Semi-variograms

Recall that the semi-variogram is given by

$$2\gamma(h) = \operatorname{var}(z(s+h) - z(s)) = E\big(z(s+h) - z(s)\big)^2,$$

If γ(h) = γ(||h||) then the semi-variogram is isotropic, meaning that it is invariant under rotation. Alternatively, the correlation between two points is a function not only of distance but of direction. This may be the case, for example, for pollutant-dispersion in a narrow valley. When the correlation is a function of direction and distance both, it is said to exhibit anisotropy. The empirical semi-variogram can be calculated as:

$$\gamma_{ij} = \frac{1}{2}\frac{1}{n}\sum_{i \neq j}\left(z_i - z_j\right)^2$$

The empirical semi-variograms can be plotted to explore the characteristics of the model and to choose a parametric serial correlation model to fit the data.

Parametric models of spatial correlation

In all the following models, *h* is the distance between two locations, *θ* is the semi-variogram for the data, and *a* is the "range"—the distance beyond which there is no longer any spatial correlation.

a. Spherical

$$\gamma(h) = \begin{cases} \theta\left[\dfrac{3}{2}\dfrac{h}{\theta} - \dfrac{1}{2}\left(\dfrac{h}{\theta}\right)^3\right] & 0 \le h \le a \\ \theta & a < h \end{cases}$$

b. Exponential

$$\gamma(h) = \theta\left[1 - \exp(-h/a)\right]$$

c. Gaussian

$$\gamma(h) = \theta\left[1 - \exp\left[-3\left(\frac{h}{a}\right)^2\right]\right]$$

d-Rational Quadratic

$$\gamma(h) = \theta \frac{19\left(\frac{h}{a}\right)^2}{1 + 19\left(\frac{h}{a}\right)^2}$$

The previous definitions make clear that some important decisions must be made in order to estimate the model in practice:

1. In order for the problem to be tractable, one must choose a maximum distance.
2. For the matrix to be finite, it is necessary to group observations into bins; e.g. we calculate the variance between s_0 and points within 1 mile, between 1 and 2 miles, 2 and 3 miles, etc.
3. One must look for anisotropy.

Empirical Estimation

The estimation consists of several steps

1. Test data for evidence of spatial correlation.
2. Data exploration:
    a. Test for normality of z. If z is not normal then transform z using the most appropriate transformation. For example a log(z), or box-cox transformation.
    b. Remove trends (if any).
    c. Calculate and plot the empirical semi-variogram as a function of the distance
3. Fit a parametric model of serial correlation. This involves choosing a model, a lag size, the number of lags, and deciding whether to correct for anisotropy.
4. Generate predictions and measures of fit.
5. Repeat steps 3 and 4 until there is no longer an improvement in the fit.

IDW versus Kriging

The Inverse Distance Weighting (IDW) value for a location Z is the weighted average of values within a given diameter of Z, where the weight is given by 1/distance. IDW is calculated as follows:

$$Z = \frac{\sum_{i=1}^{n} \frac{Z_i}{h_{ij}^{\beta}}}{\sum_{i=1}^{n} \frac{1}{h_{ij}^{\beta}}}$$

where h_{ij} is the distance from location *j* to *i*. In the applications here β was always set to 1. Note that IDW makes an assumption about the type of serial correlation in the data, and that assumption is that serial correlation decays inversely proportionally to distance. Kriging estimates the serial correlation instead.

Testing for spatial correlation

There are several tests for spatial correlation. The following three tests are well known and commonly used. Their properties are slightly different. For all test statistics, *N* refers to the number of observations in the data, and the subscripts refer to the location. The weights w_{ij} are chosen by the researcher and are generally some inverse function of the distance between points. The variance is not reported here, but it depends on whether it is assumed that the underlying data follow a normal process or a random process.

A. Moran's I

The formula for Moran's I is given by:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$$

The expected value of Moran's I under the assumption of no global correlation is given by:

$$E(I) = \frac{-1}{(N-1)}$$

Values greater than *E(I)* indicate positive spatial correlation; values les than *E(I)* indicate negative spatial correlation. The hypothesis of random distribution is rejected if

$$Z = \left|\frac{I - E(I)}{\sqrt{Var(I)}}\right| > 1.96$$

B. Geary's C

The formula for Geary's C is given by:

$$c = \frac{(N-1)}{2\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} w_{ij}\left(x_i - x_j\right)^2}{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}$$

The expected value for Geary's C is 1. Values less than 1 indicate positive spatial correlation, and values greater than one indicate negative spatial correlation. The hypothesis of random distribution is rejected if

$$Z = \left|\frac{c - 1}{\sqrt{Var(c)}}\right| > 1.96$$

C. Getis and Ord's G

The formula for Getis and Ord's G is given by:

$$G = \frac{\sum_{i\neq j} \hat{w}_{ij} x_i x_j}{\sum_{i\neq j} x_i x_j}$$

The weights are either 0 or 1, depending on distance. All the values of x are positive.

The expected value under the assumption of no global correlation is:

$$E(G) = \frac{\sum_{i \neq j} \hat{w}_{ij}}{N(N-1)}$$

The hypothesis of random distribution is rejected if

$$Z = \left| \frac{G - E(G)}{\sqrt{Var(G)}} \right| > 1.96$$

Appendix Table D: Tests of global spatial correlation, 1988

Pollutant	interval		Moran's I				Geary's C			Getis and Ord's G			
			I	E(I)	sd(I)	Z(I)	C	sd(C)	Z(C)	G	E(G)	sd(G)	Z(G)
CO	0	3218	1.05	-0.0024	0.32	**3.27**	0.69	0.55	-0.56	0.002	0.001	0.00	**8.115**
	0	8046	0.90	-0.0024	0.24	**3.76**	0.69	0.41	-0.76	0.004	0.002	0.00	**7.294**
	0	24139	0.72	-0.0024	0.18	**4.03**	0.70	0.31	-0.97	0.009	0.008	0.00	**4.077**
	0	48278	0.65	-0.0024	0.16	**4.13**	0.71	0.27	-1.08	0.018	0.016	0.00	**3.664**
NO_2	0	3218	1.22	-0.0035	0.22	**5.52**	0.13	0.43	**-1.99**	0.001	0.001	0.00	-0.075
	0	8046	1.18	-0.0035	0.16	**7.50**	0.14	0.32	**-2.71**	0.002	0.002	0.00	**2.846**
	0	24139	1.17	-0.0035	0.09	**12.76**	0.21	0.19	**-4.06**	0.014	0.009	0.00	**8.821**
	0	48278	1.20	-0.0035	0.07	**16.54**	0.28	0.16	**-4.58**	0.031	0.019	0.00	**12.158**
O_3	0	3218	0.23	-0.0014	0.40	**0.58**	1.07	0.81	0.09	0.000	0.000	0.00	-1.598
	0	8046	0.22	-0.0014	0.19	**1.18**	0.88	0.39	-0.31	0.000	0.000	0.00	-0.337
	0	24139	0.39	-0.0014	0.06	**6.02**	0.68	0.15	**-2.18**	0.004	0.004	0.00	**3.565**
	0	48278	0.40	-0.0014	0.04	**10.11**	0.70	0.10	**-2.99**	0.013	0.012	0.00	**6.688**
Pb	0	3218	0.64	-0.0038	0.22	**2.87**	0.88	1.39	-0.09	0.030	0.003	0.00	**10.737**
	0	8046	0.60	-0.0038	0.21	**2.90**	0.87	1.29	-0.10	0.034	0.005	0.00	**8.596**
	0	24139	0.55	-0.0038	0.19	**2.90**	0.83	1.20	-0.14	0.037	0.013	0.01	**4.746**
	0	48278	0.53	-0.0038	0.18	**2.91**	0.85	1.15	-0.13	0.051	0.022	0.01	**4.010**
PM10	0	3218	0.57	-0.0010	0.20	**2.85**	0.28	0.41	**-1.78**	0.000	0.000	0.00	1.374
	0	8046	0.45	-0.0010	0.16	**2.80**	0.27	0.33	**-2.25**	0.001	0.001	0.00	**3.484**
	0	24139	0.36	-0.0010	0.11	**3.13**	0.38	0.23	**-2.65**	0.005	0.004	0.00	**3.512**
	0	48278	0.34	-0.0010	0.09	**3.70**	0.44	0.19	**-2.99**	0.012	0.011	0.00	**3.423**
SO_2	0	3218	1.45	-0.0018	0.27	**5.29**	0.40	0.47	-1.26	0.001	0.001	0.00	**9.894**
	0	8046	1.29	-0.0018	0.21	**6.21**	0.39	0.36	**-1.68**	0.004	0.002	0.00	**11.862**
	0	24139	1.17	-0.0018	0.16	**7.38**	0.44	0.28	**-2.04**	0.012	0.007	0.00	**14.545**
	0	48278	1.09	-0.0018	0.13	**8.23**	0.49	0.23	**-2.23**	0.030	0.016	0.00	**16.967**

Figures in bold are significant at the 5% level (two tailed test). For Moran's I and Geary's C, the weights are always the inverse distance (friction parameter =1) if the observation is within the distance interval, and 0 otherwise. For Getis and Ord's statistic, weights are either 0 or 1 (1 if the observation is within interval). Coordinates are expressed in Universal Transverse Mercators, (UTMs, rectangular metric mapping coordinate system used instead of latitude and longitude, where x and y are expressed in meters). Therefore distances are expressed in meters (3,218 meters = 2.5 miles; 8,046 meters = 5 miles; 24,139 meters = 15 miles and 48, 278 meters = 30 miles).

Appendix E Table: Models of spatial correlation used for each pollutant

Variable[1]	Method[2]	Transformation	Declustering method/ trend	Approxi-mation	Anisotropy	Model	Lags[3]	Neighbor-hood[3]
CO	simple co-Kriging using temperature, precipitation and elevation (elevation not used in 2000)	Normal score/declust	Polygonal	Linear	Yes	Exponential	.3/9 (.125/9 in 2000)	5/2 X
NO_2	Ordinary Kriging	None	None	n/a	No	Spherical	0.318/12 to.485/12	2/1 X
O_3	ordinary co-Kriging using temperature, precipitation and wind direction	None	2nd	60%	No	Gaussian	0.023/13 to 0.071/13	1/1 open
PB	Ordinary Kriging	None	None	n/a	yes (90,91,95,96,00) no otherwise	Spherical	.00619/12 to 4.7/9	5/2X, 22/XX, 6/6 open, 5/3X
PM10	ordinary co-Kriging using temperature, precipitation and wind direction	Log	1st	50%	No	Exponential	2.3/7	5/2 X
SO_2	ordinary Kriging	None	None	n/a	Yes	Exponential	1.103 to 1.897/12	5/2 X
TSP	ordinary Kriging	None	None	n/a	No	Exponential	0.144/12 to .718/12	1/1 X
Temperature	ordinary Kriging	Log	1st	100%	Yes	Spherical	.3/7	5/2 X
Precipitation	ordinary Kriging	None	1st	100%	Yes	Rational quadratic	.3/19	7/2 open

1. When more than one measurement was available at a given location, the mean of the measurements was assigned to the location and used in the predictions.
2. Covariates were transformed as follows: Temperature with log transformation and with first order trend; precipitation without transformation and with first order trend; elevation without transformation (order of trend not applicable in simple co-Kriging); wind direction without transformation and with second order trend.
3. When a range is specified, it means that the lag/neighborhood was chosen differently each year to obtain the best fit.

Appendix F: Goodness of fit measures for spatial predictions

Variable	Year									
	1988	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**2000**
CO										
Coefficient	0.2	0.2	0.23	0.3	0.29	0.27	0.29	0.31	0.34	0.41
Mean	0.03	0.06	0.03	0.04	0.04	0.05	0.04	0.05	0.04	0.04
RMSE	0.57	0.55	0.48	0.46	0.45	0.43	0.39	0.37	0.34	0.28
Av. Std error	0.59	0.62	0.54	0.53	0.49	0.49	0.42	0.39	0.32	0.29
Mean stndized	0.05	0.1	0.05	0.06	0.06	0.07	0.07	0.12	0.11	0.11
RMSE stndized	0.95	0.87	0.9	0.89	0.94	0.91	0.94	0.92	1.07	1.00
# of monitors					416					527
NO2										
Coefficient	0.75	0.73	0.75	0.75	0.73	0.73	0.73	0.73	0.72	0.62
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Av. Std error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Mean stndized	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.05
RMSE stndized	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
# of monitors					284					443
O3										
Coefficient	0.69	0.7	0.72	0.75	0.69	0.82	0.78	0.8	0.78	0.77
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Av. Std error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Mean stndized	0.00	-0.03	-0.01	-0.02	-0.04	-0.05	-0.05	-0.05	-0.04	-0.04
RMSE stndized	1.00	1.00	1.00	1.00	0.93	0.93	0.90	0.90	0.93	1.01
# of monitors					716					1137
PB										
Coefficient	0.32	0.33	0.32	0.43	0.09	0.27	0.21	0.25	0.37	0.43
Mean	0.01	0.01	0.01	0.00	0.05	0.01	0.00	0.01	0.01	0.01
RMSE	0.78	0.85	0.73	0.71	0.85	0.58	0.60	0.62	0.69	0.37
Av. Std error	0.84	1.14	0.80	0.78	0.86	0.65	0.60	0.73	0.78	0.39
Mean stndized	0.00	0.00	0.00	0.00	0.06	0.01	0.00	0.01	0.01	0.03
RMSE stndized	1.00	1.00	1.01	1.02	0.99	1.00	1.01	1.00	1.00	0.97
# of monitors					263					201
PM10										
Coefficient	0.36	0.39	0.43	0.45	0.4	0.43	0.41	0.42	0.36	0.33
Mean	-0.15	-0.2	-0.13	-0.1	-0.12	-0.09	-0.05	-0.06	-0.08	-0.43
RMSE	9.20	9.43	7.88	7.29	6.44	6.35	6.19	6.16	5.94	11.07
Av. Std error	9.05	8.59	7.44	7.24	6.32	6.37	6.71	6.36	5.90	8.70
Mean stndized	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.04
RMSE stndized	1.00	1.10	1.05	1.04	1.04	1.05	0.96	1.02	1.02	1.06
# of monitors					1053					1190

Appendix F continued

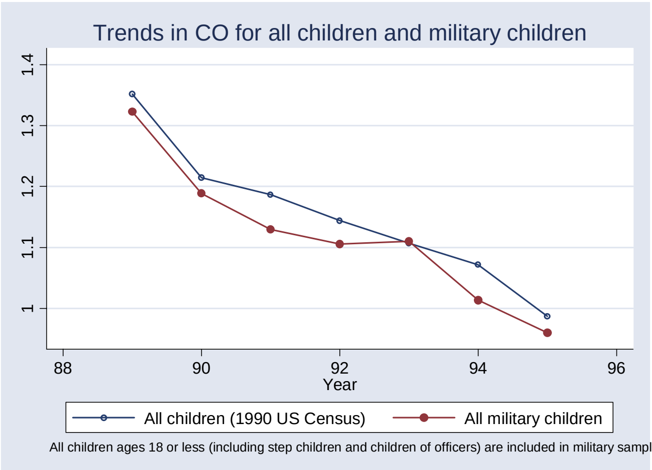
Variable	Year									
	1988	1989	1990	1991	1992	1993	1994	1995	1996	2000
SO2										
Coefficient	0.62	0.67	0.64	0.69	0.69	0.71	0.70	0.61	0.61	0.67
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Av. Std error	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean stndized	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01
RMSE stndized	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	0.91
# of monitors					563					607
TSP										
Coefficient	0.55	0.6	0.53	0.54	0.55	0.56	0.6	0.57	0.53	n/a
Mean	0.16	0.02	-0.03	0.08	0.08	0.16	0.31	0.08	0.14	n/a
RMSE	15.15	14.57	13.54	13.34	12.35	12.7	12.84	12.71	12.97	n/a
Av. Std error	15.22	14.66	13.59	13.46	12.37	12.82	13.03	12.79	12.76	n/a
Mean stndized	0.00	-0.01	-0.01	0.00	-0.01	0.00	0.01	0.00	0.00	n/a
RMSE stndized	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.02	n/a
# of monitors					416					
Temperature										
Coefficient	0.96	0.97	0.97	0.97	0.96	0.97	0.97	0.97	0.97	0.97
Mean	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00
RMSE	2.06	2.03	2.07	2.05	2.06	2.06	2.05	2.03	2.00	2.04
Av. Std error	2.07	2.02	2.06	2.03	2.07	2.07	2.03	2.02	1.98	2.06
Mean stndized	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE stndized	1.00	1.00	1.01	1.02	1.00	1.00	1.00	1.00	0.99	0.99
# of monitors	1219	1120	1218	1218	1219	1219	1219	1219	1220	1217
Precipitation										
Coefficient	0.90	0.92	0.93	0.91	0.92	0.88	0.90	0.87	0.91	0.86
Mean	-0.03	0.06	0.06	-0.02	0.03	0.05	-0.01	0.00	0.10	0.04
RMSE	5.89	5.92	6.44	6.30	5.91	5.94	6.31	7.21	7.12	5.70
Av. Std error	5.78	6.53	7.16	6.45	5.92	5.66	6.04	6.38	6.95	5.30
Mean stndized	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.01
RMSE stndized	1.00	0.91	0.90	0.96	0.99	1.02	1.02	1.09	1.00	1.05
# of monitors	952	948	938	938	935	928	920	915	912	876

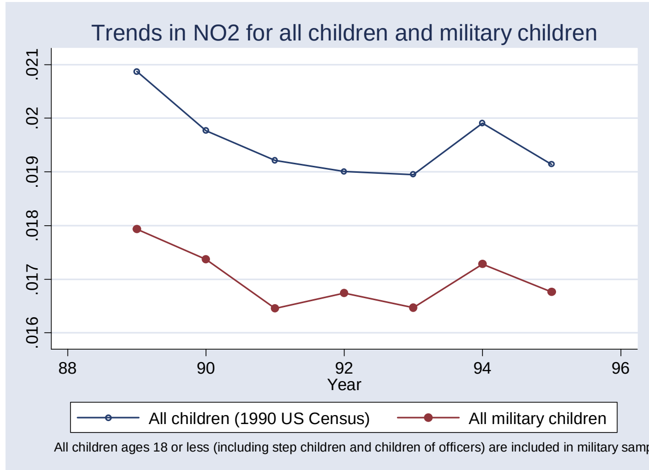
Appendix G: Comparing pollution exposure of children under 18 in the military and in the general population

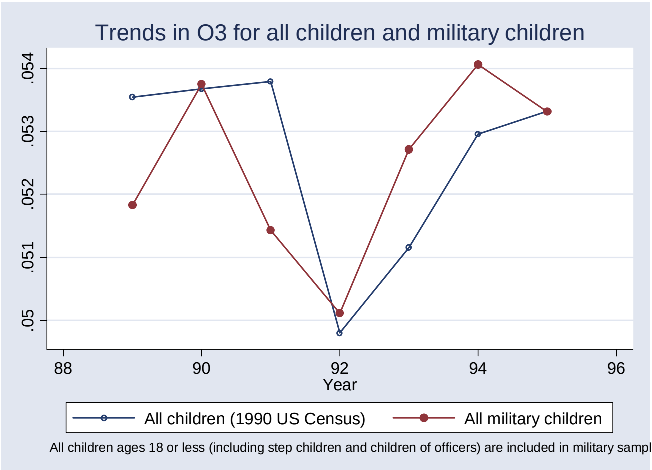
	Mean	S.D.	Min.	Max.
Panel A: Pollution means weighted by US population ages 18 or younger, 1989-1995				
CO	1.152	0.116	0.987	1.352
NO_2	0.020	0.001	0.019	0.021
O_3	0.053	0.002	0.050	0.054
PM10	28.462	2.526	25.832	32.651
SO_2	0.006	0.001	0.005	0.007
Pb	0.150	0.020	0.112	0.175
Panel B: Pollution means for military children ages 18 or younger, 1989-1995				
CO	1.107	0.207	0.514	2.270
NO_2	0.017	0.005	0.005	0.049
O_3	0.052	0.008	0.012	0.147
PM10	26.898	3.752	13.094	61.292
SO_2	0.005	0.002	0.001	0.019
Pb	0.142	0.192	0.006	2.281

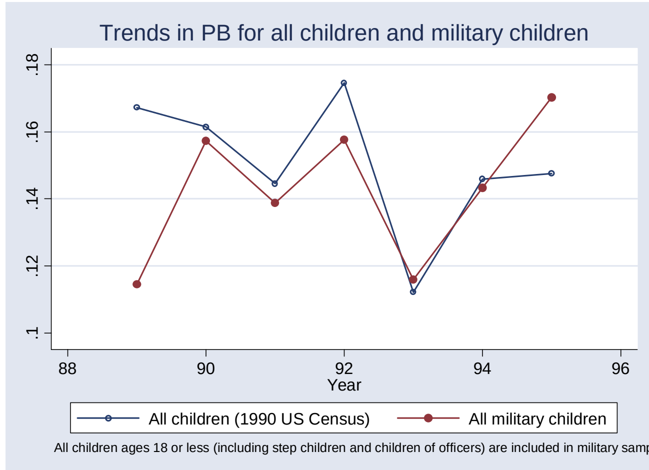
Notes: population counts for ages 18 or younger come from the 1990 Census (Summary Tape files 3C) at the zip-code level. Pollution means for the US Population were created by averaging Kriging predictions at the zip-code level, using the 1990 population as weights.

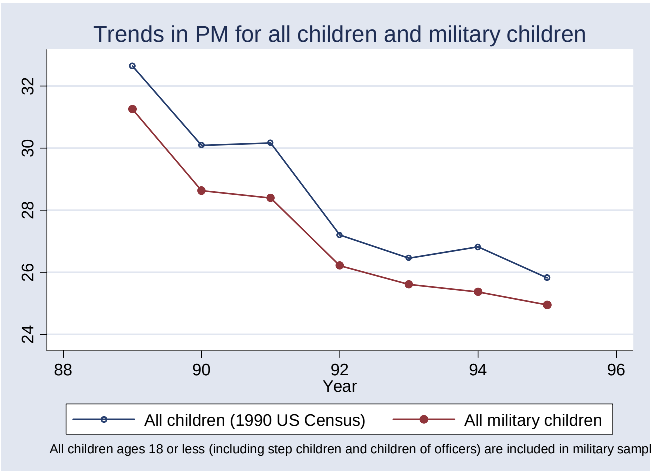
Appendix H: Comparing pollution trends in the population and in the military (ages 18 and under)











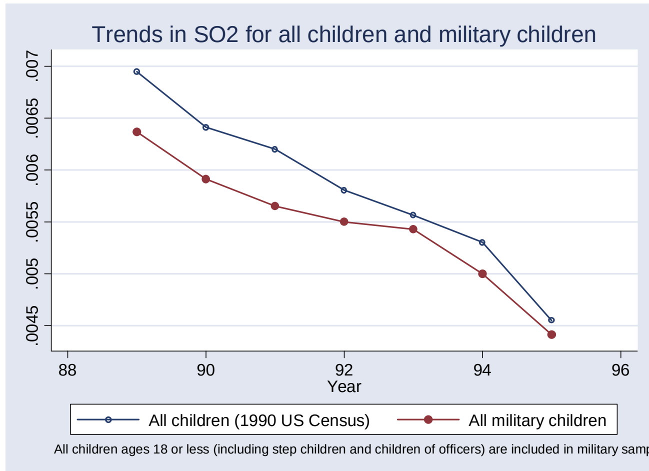
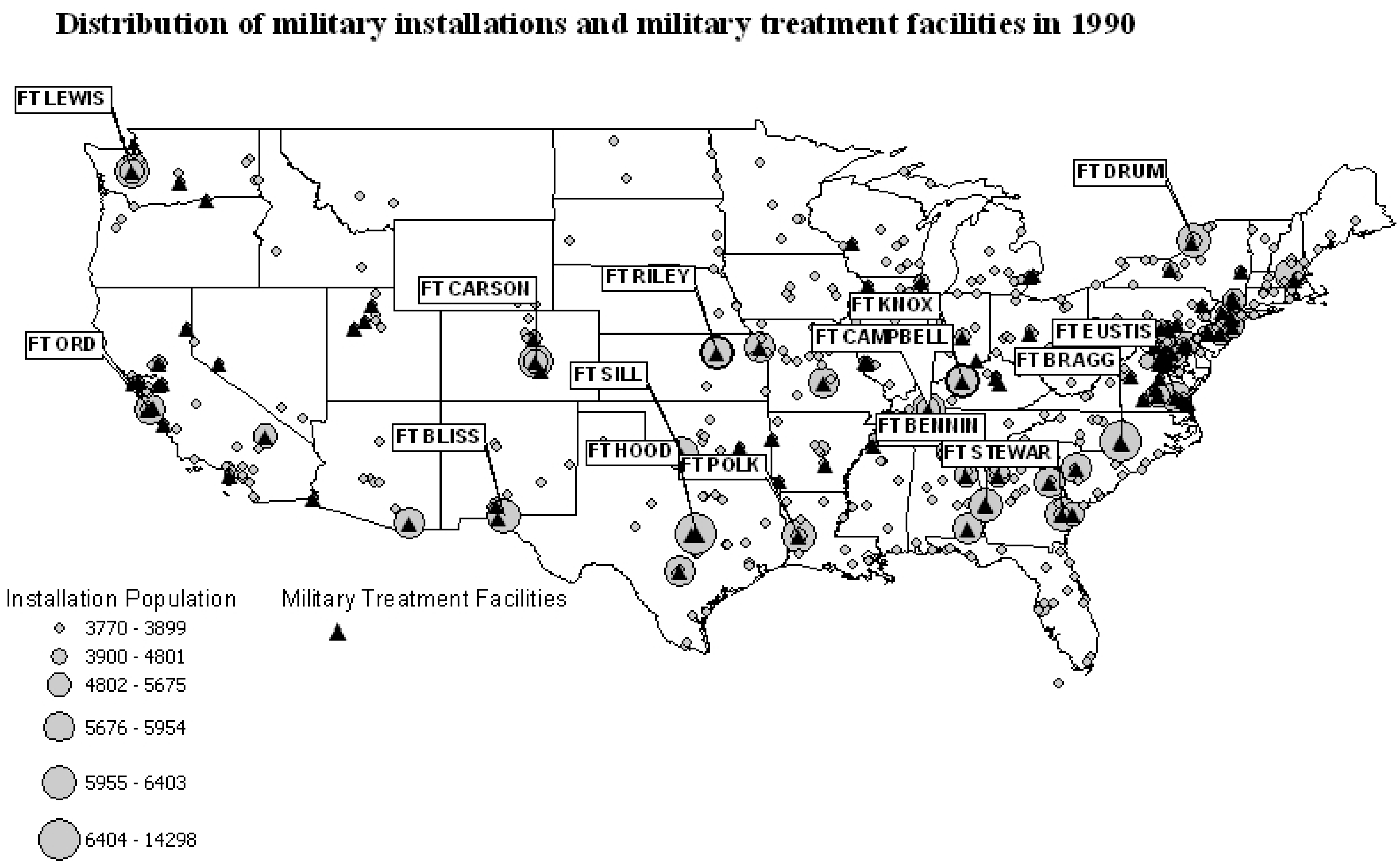
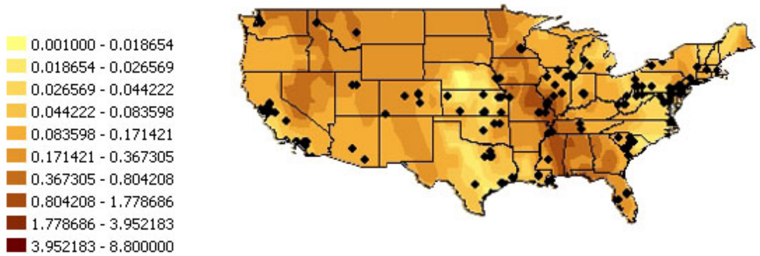


Figure 1

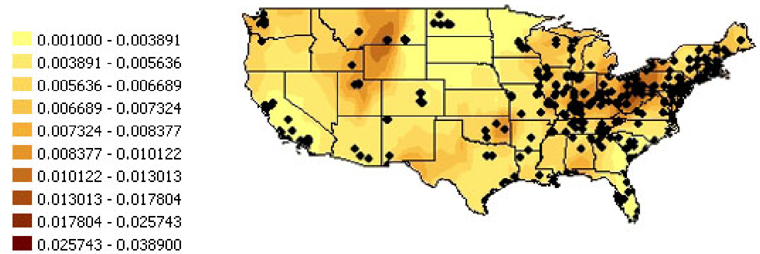


Base sizes calculated from sample provided by DMDC (includes all dependents, including dependents of officers and stepchildren).

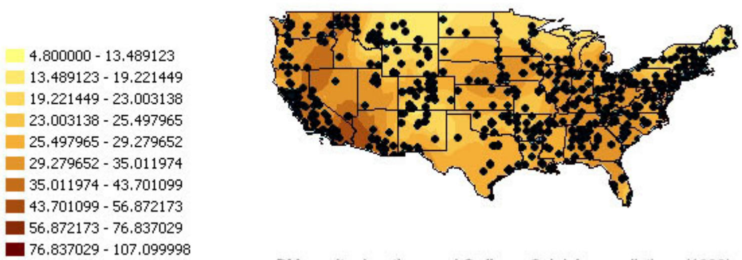
Figure 2: Predicted distribution for the 6 major air pollutants in 1990



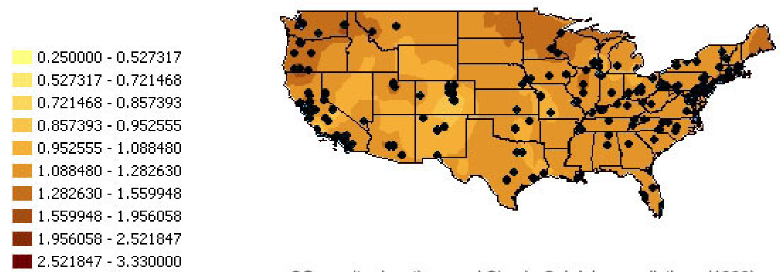
Pb monitor locations and Ordinary Kriging predictions (1990)



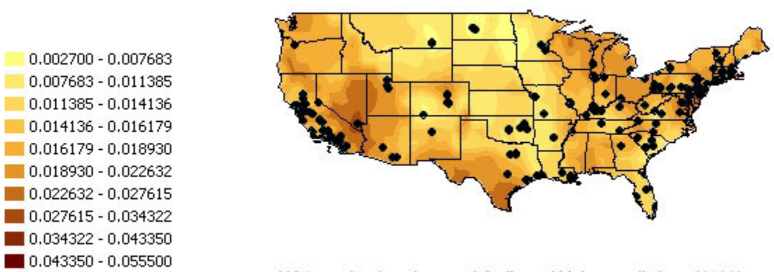
So2 monitor locations and Ordinary Kriging predictions (1990)



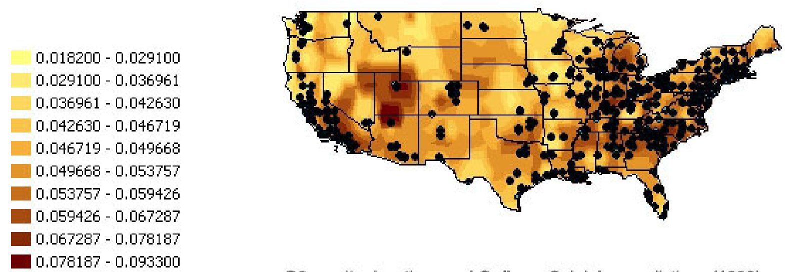
PM monitor locations and Ordinary Cokriging predictions (1990)



CO monitor locations and Simple Cokriging predictions (1990)

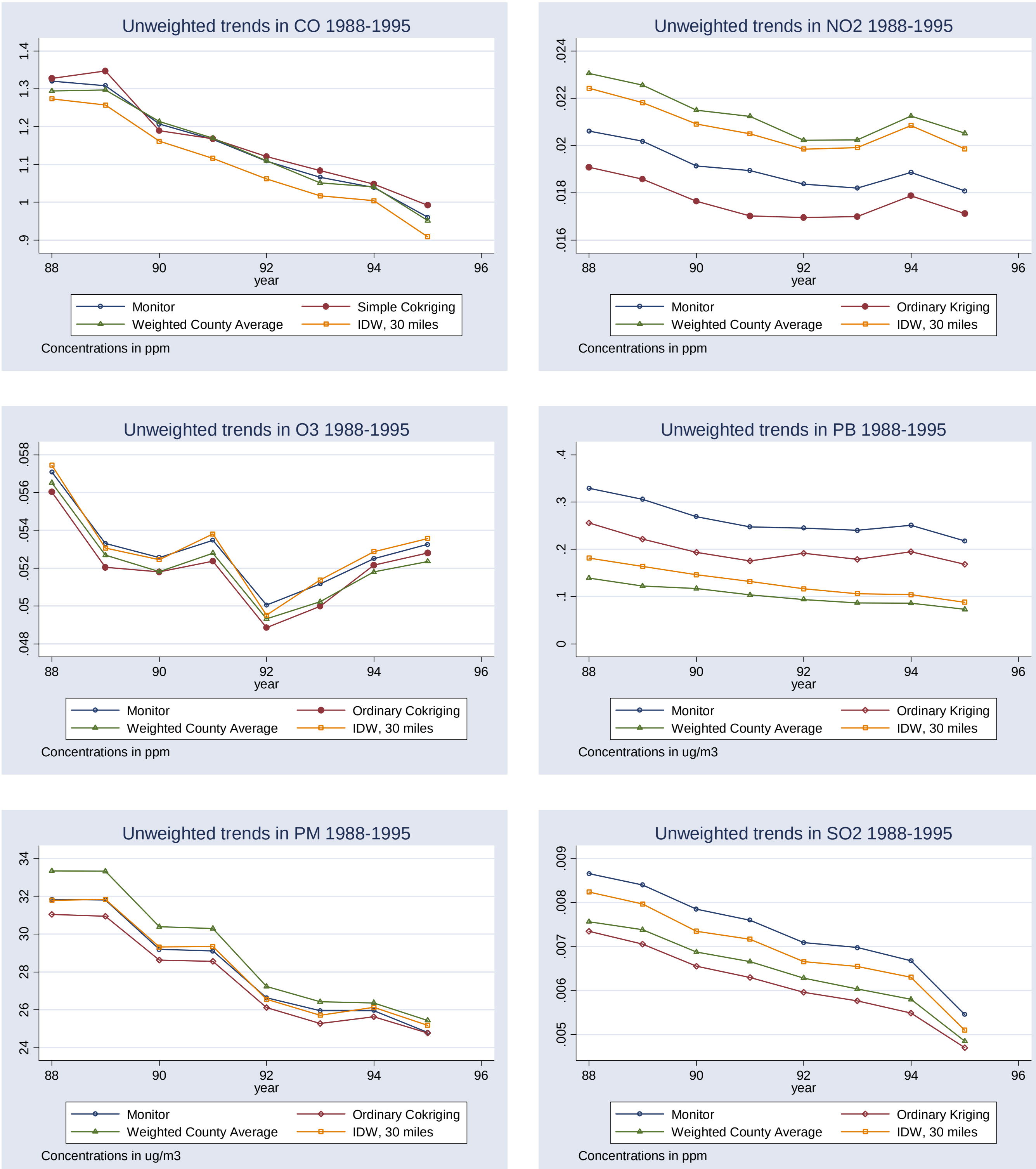


NO2 monitor locations and Ordinary Kriging predictions (1990)



O3 monitor locations and Ordinary Cokriging predictions (1990)

Figure 3: Comparing trends from different prediction methods



Note: Kriging predictions include predictions for all zip codes in the US. No distance to monitor restriction was made.

Figure 4

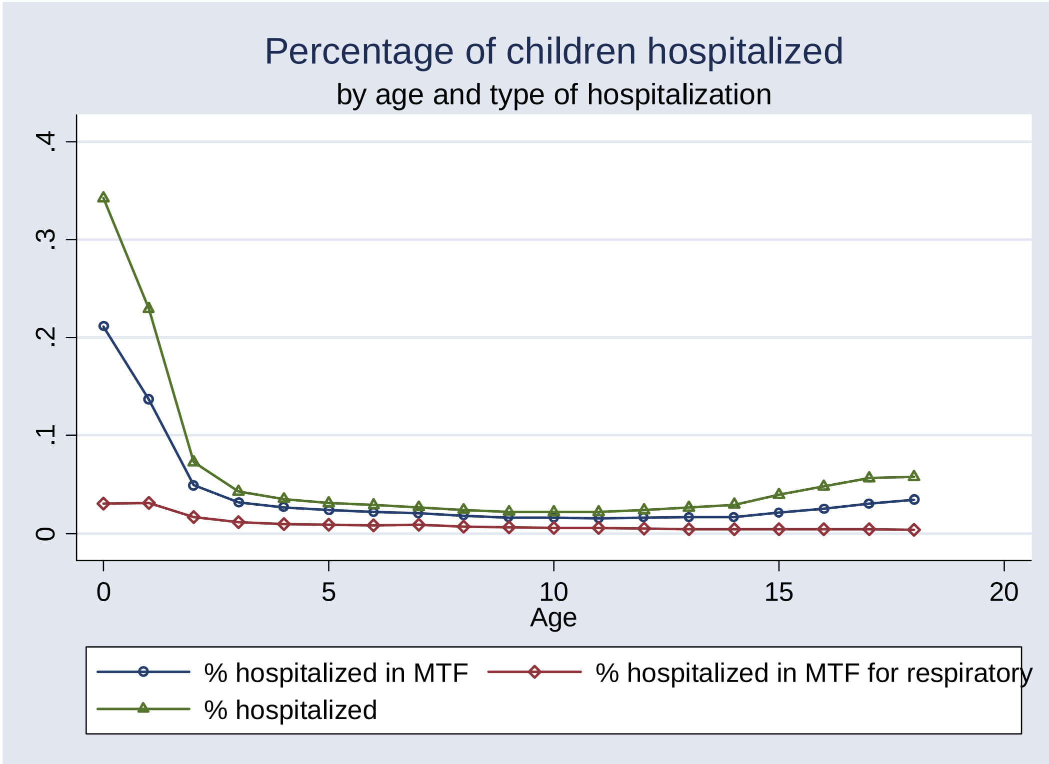


Figure 5

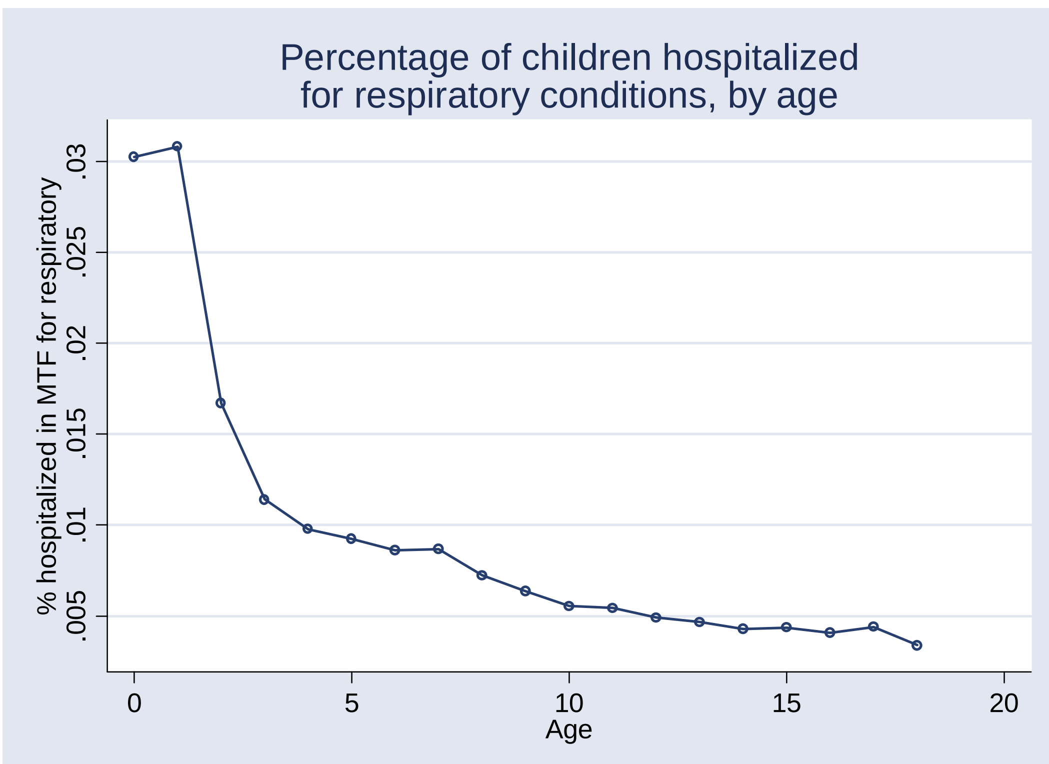


Figure 6

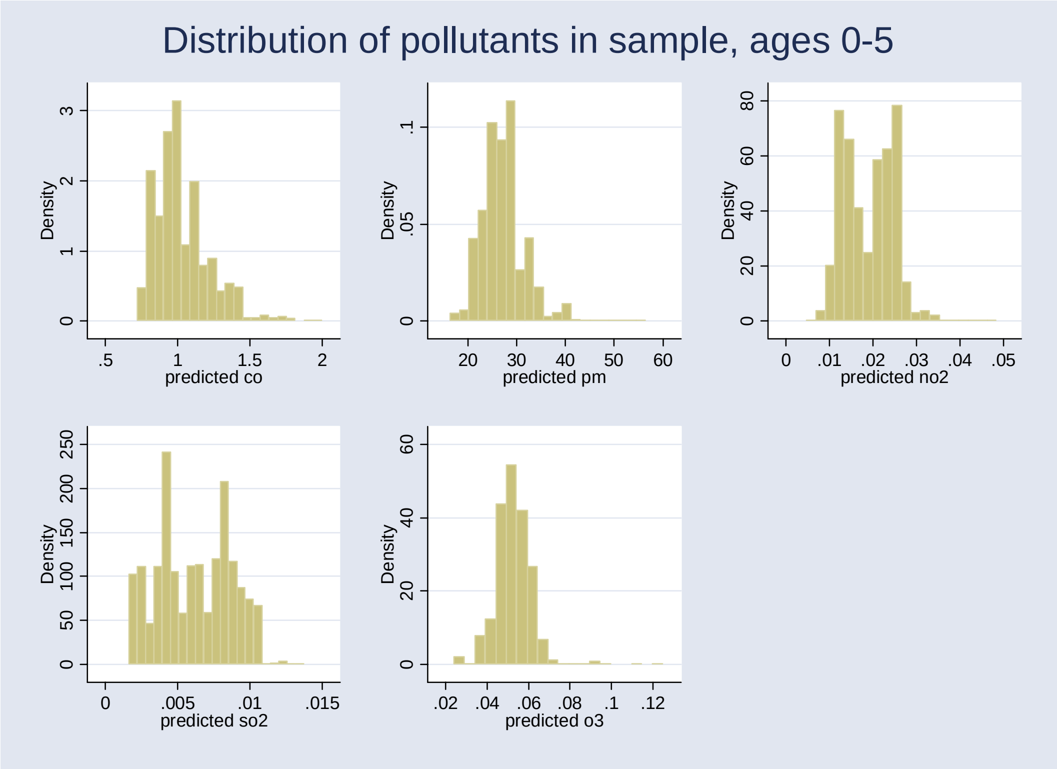
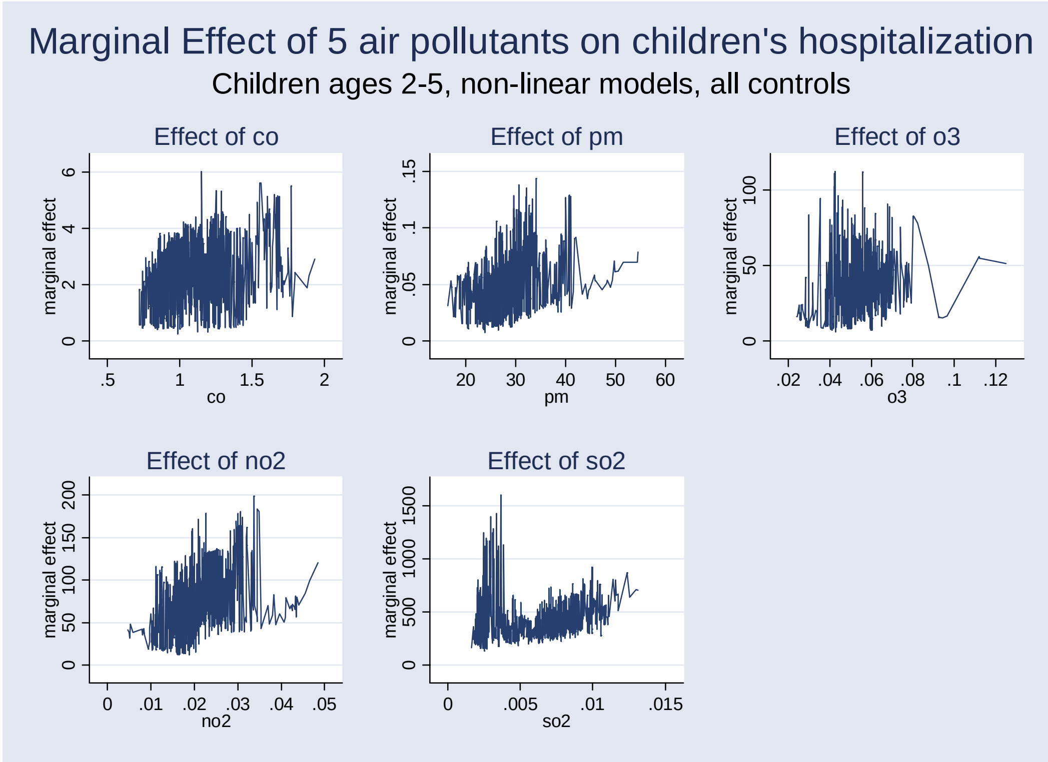

Distribution of pollutants in sample, ages 0-5
Density
predicted co
predicted pm
predicted no2
predicted so2
predicted o3

Figure 7a: Implied Marginal Effects from non-linear and interacted model, children ages 2 to 5.

Full sample



Dropping pollutant values above the 90th percentile

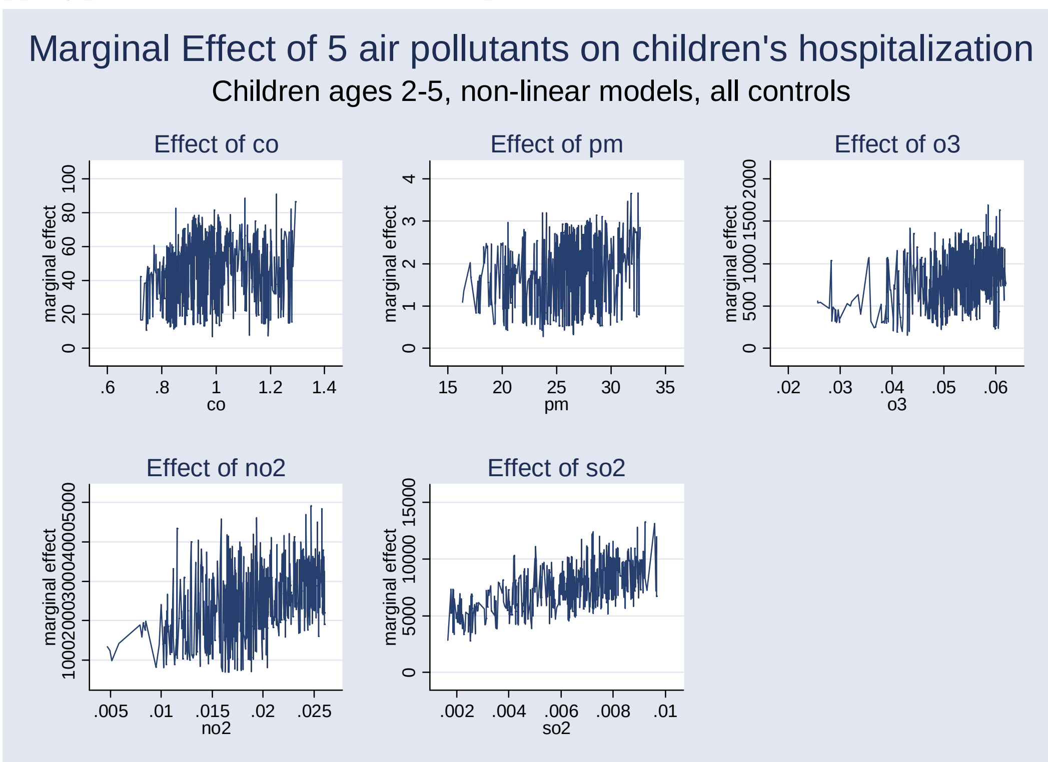
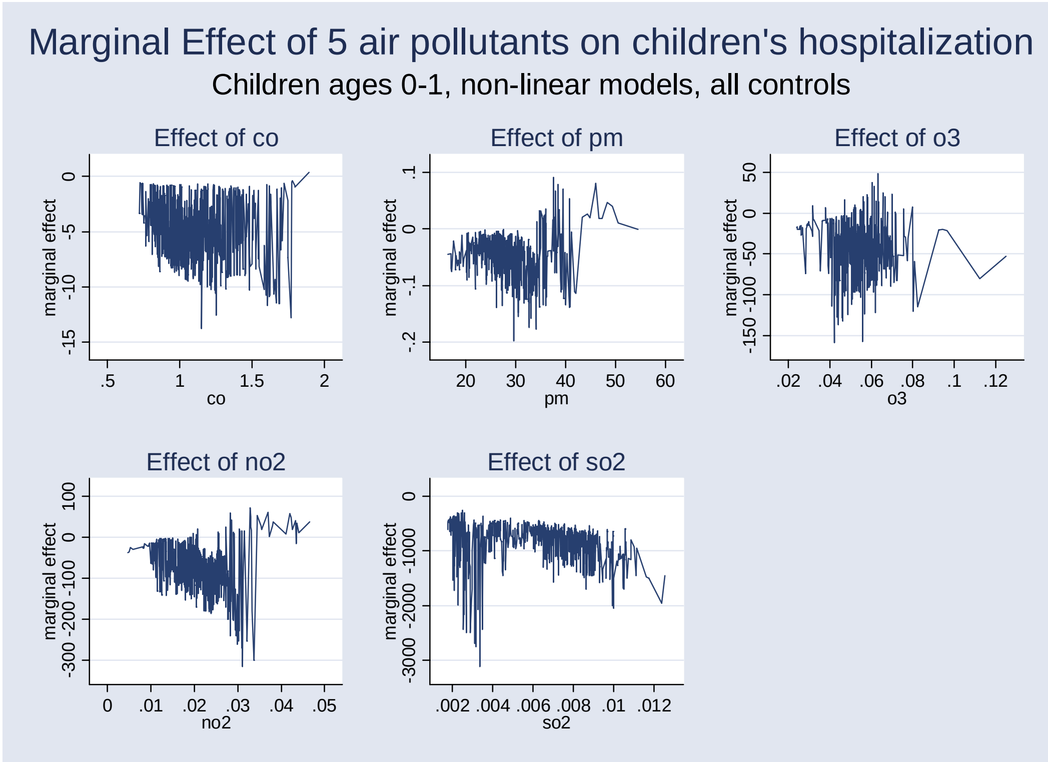


Figure 7b: Implied Marginal Effects from non-linear and interacted model, children ages 0 to 1.

Full Sample



Dropping pollutants values above the 90th percentile

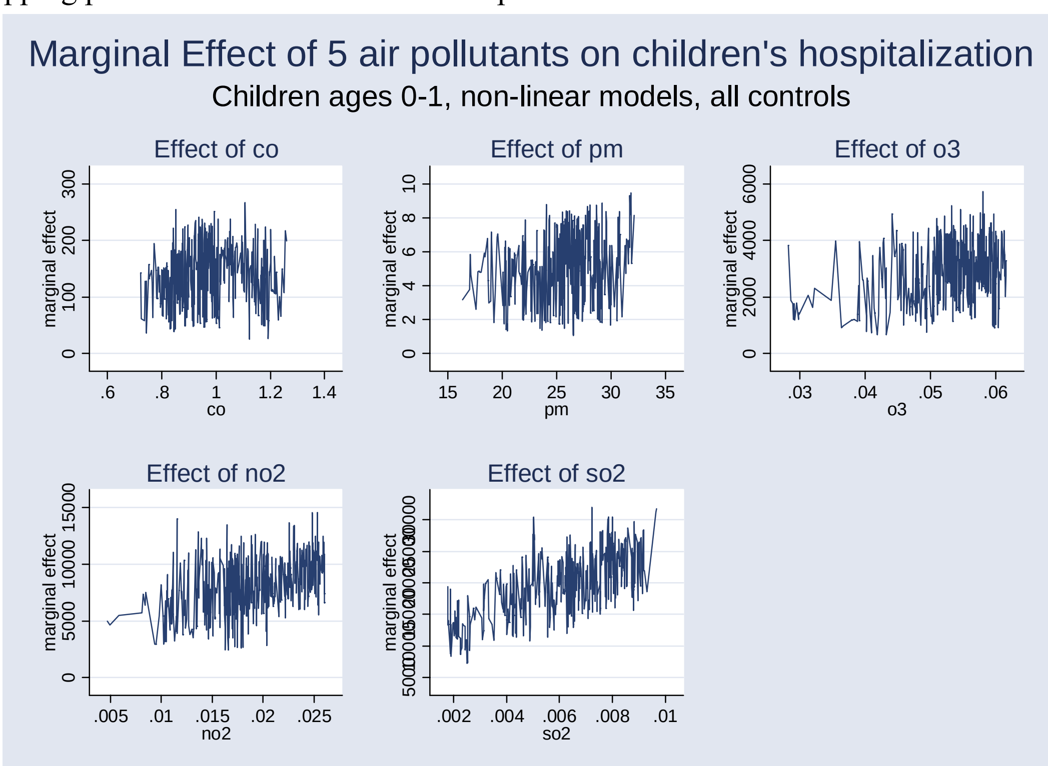


Table 1: Summary Statistics for Children ages 0 to 5

Variable	Obs	Mean	Std. Dev.	Min	Max
Children's characteristics (N=95,909)					
Year	165411	92.08	1.98	89	95
Male=1	165411	0.51	0.50	0	1
Age	165411	2.66	1.61	0	5
White, non Hispanic=1	165411	0.60	0.49	0	1
Number of years observed in sample	165411	3.20	1.60	1	8
Moved in year =1 (observed consecutively)	101284	0.29	0.46	0	1
Moved in year =1 (not observed consecutively)	111117	0.32	0.47	0	1
Gone next year =1	165411	0.26	0.44	0	1
Hospitalized at least once during year	165411	0.11	0.31	0	1
Hospitalized in MTF	165411	0.07	0.25	0	1
Hospitalized in MTF for respiratory condition	165411	0.02	0.13	0	1
Hospitalized in MTF for external cause	165411	0.0038	0.0615	0	1
Hospitalized in MTF for non-respiratory condition	165411	0.05	0.21	0	1
Father and mother characteristics (N=68,676)					
Number of dependents (including wife)	165411	2.43	1.20	1	15
Some college or higher	164309	0.12	0.32	0	1
Father's age	165352	29.27	5.27	17	55
Mother hospitalized at least once during year	165411	0.21	0.40	0	1
Mother hospitalized in MTF	165411	0.14	0.35	0	1
Mother hospitalized in MTF for pregnancy	165411	0.11	0.31	0	1
Total active military service in months	165311	106.75	61.74	1	417
Number of months since reenlistment	160343	30.07	26.75	0	438
Has been in the military fewer than 6 years =1	165411	0.25	0.43	0	1
Increased rank (observed consecutively) =1	122543	0.18	0.39	0	1
Increased education (observed consecutively) =1	122543	0.02	0.14	0	1

Sample: children ages 0 to 5 of married men enlisted in the army and stationed in the Continental US between 1989 and 1995, excluding stepchildren, children of officers, and those without access to an MTF. The sample is further restricted to individuals in bases with at least one monitor for each pollutant within 50 miles. Observations with missing values for age, gender, occupation (PMOS), rank, and duty base identifier were also dropped.

Table 1 continued: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Base characteristics (N=177)					
Temperature (F)	165411	56.317	5.638	45.09	67.51
Rain (inches)	165411	35.208	13.667	11.72	71.91
Number of fathers at base	165411	6166.603	4477.597	1	14990.00
Percent of enlisted personnel requesting this base	165411	2.877	2.713	0	8.40
Distance to closest city (miles)	165411	3.686	4.399	0.11	34.42
Distance to closest city with pop 50K (miles)	165411	13.995	11.952	0.11	54.98
Distance to closest city with pop 100K (miles)	165411	19.136	19.156	0.239	103.22
Distance to MTF (miles)	165411	0.056	0.112	0	0.58
Pollution					
Average annual mean					
Carbon Monoxide (CO) (ppm)	165411	1.028	0.187	0.722	1.934
Nitrogen Dioxide (NO_2) (ppm)	165411	0.019	0.006	0.005	0.049
Ozone (O_3) (ppm)	165411	0.053	0.008	0.024	0.125
Particulate matter (PM10, particles with diameter <=10 micrometers) (ug/m^3)	165411	27.241	4.162	16.387	54.606
Sulfur Dioxide (SO_2) (ppm)	165411	0.006	0.003	0.002	0.013
Lead (Pb) (ug/m^3)	165411	0.097	0.125	0.008	2.281
Monitor information					
% with county predictions for all pollutants	165411	0.1841111	0.3875759	0	1
% with IDW15 predictions for all pollutants	165411	0.0522275	0.2224861	0	1
% with IDW30 predictions for all pollutants	165411	0.4977843	0.4999966	0	1
Average characteristics at base (from largest possible sample, includes children of all ages)					
% officers at base	165411	0.180	0.153	0	0.98
% stepchildren at base	165411	0.105	0.026	0	0.80
Average total active months in service at base	165411	155.549	18.713	27	279.52
Average number of dependents at base	165411	2.817	0.128	1	8.00
Average dad age at base	165411	34.210	1.783	25	45.34
Average children age at base	165411	8.810	0.964	1	15
% white at base	165411	0.625	0.093	0	1
% college at base	165411	0.312	0.159	0	1
% newly enlisted at base	165411	0.112	0.054	0	1
% gone next year at base	165411	0.269	0.101	0	1
% children hospitalized at base	165411	0.058	0.017	0	1
% children hospitalized at MTF at base	165411	0.037	0.016	0	1
% children hospitalized at MTF at base for respiratory condition	165411	0.010	0.005	0	0.250
% children hospitalized at MTF at base for external causes	165411	0.004	0.002	0	0.071

Notes: ug/m^3 stands for micrograms per cubic meter; ppm stands for parts per million.
Sample: children ages 0 to 5 of married men enlisted in the army and stationed in the continental US between 1989 and 1995, excluding stepchildren, children of officers and those without access to a MTF. The sample is further restricted to individuals in bases with at least one monitor for each pollutant within 50 miles. Observations with missing values for age, gender, occupation (PMOS), rank, and duty base identifier were also dropped.

Table 2a: Testing Random Relocations, conditional on rank and occupation interactions
Sample: Children ages 0 to 5 who moved

Variable	Obs	Mean	Std. Dev.
<u>Relocation to any base (excluding foreign), regardless of current base(*)</u>			
One equation per base, control for rank*pmos*year D=1 if p<0.05	380	0.066	0.248
Relocation to bases in study, regardless of current base			
One equation per base, control for rank*pmos*year D=1 if p<0.05	118	0.017	0.130

Linear probability models. Errors clustered at the sponsor level.

Control variables tested include age, gender, health variables (whether hospitalized, hospitalized in MTF, hospitalized in MTF for respiratory condition), father/sponsor's controls (number of months since last enlistment, total active months in the military, age, white dummy, college degree, number of dependents, enlisted in the last five years), and mother's health (whether hospitalized, hospitalized in MTF, hospitalized for pregnancy).

(*) Sample restrictions are identical to those for the estimation sample, except that individuals living in all bases are included (in the final estimation sample, only those living in bases with monitors within 50 miles for all pollutants and those living within 40 miles of an MTF are included. No such sample restriction is done here.)

Table 2b: Testing whether characteristics at time t predict pollution levels at time t+1
Sample: Children ages 0 to 5 who moved

		CO	PM10	SO_2	NO_2	O_3
All years (1989-1995)						
	p-value	0.667	0.414	0.836	0.340	0.433
By year						
1989						
	p-value	0.570	0.652	0.598	0.961	0.875
1990						
	p-value	0.942	0.207	0.695	0.177	0.788
1991						
	p-value	0.866	0.584	0.902	0.417	0.533
1992						
	p-value	0.534	0.001	0.392	0.543	0.093
1993						
	p-value	0.552	0.512	0.599	0.465	0.022
1994						
	p-value	0.142	0.973	0.659	0.127	0.432
1995						
	p-value	0.383	0.805	0.891	0.337	0.613

Control variables tested include age, gender, health variables (whether hospitalized, hospitalized in MTF, hospitalized in MTF for respiratory condition), father/sponsor's controls (number of months since last enlistment, total active months in the military, age, white, college degree, number of dependents, enlisted in the last five years), and mother's health (whether hospitalized, hospitalized in MTF, hospitalized for pregnancy).

(*) Sample restrictions are identical to those for the sample, except that individuals living in all bases are included (in the final estimation sample, only those living in bases with monitors within 50 miles for all pollutants and those living within 40 miles of an MTF are included. No such sample restriction is done here.)

Table 3: Correlations between pollutants, using Kriging estimates at the base

	CO	NO_2	O_3	Pb	PM10	SO_2
Across bases (N=940 base*year observations)						
CO	1.00					
NO_2	0.51	1.00				
O_3	-0.02	0.14	1.00			
Pb	0.04	-0.10	0.20	1.00		
PM10	0.53	0.40	0.23	0.04	1.00	
SO_2	0.08	0.24	0.36	0.17	0.07	1.00
In sample (weighted by population in base N=165,411)						
CO	1.00					
NO_2	0.20	1.00				
O_3	-0.03	0.12	1.00			
Pb	0.03	-0.14	0.19	1.00		
PM10	0.55	0.09	0.14	0.12	1.00	
SO_2	0.28	0.42	0.27	0.29	0.34	1.00

Table 4: Effect of pollutants on respiratory hospitalizations, main results

Dependent variable: Child hospitalized last year for a respiratory condition (=1)	(1) Basic regression	(2) Add all parental controls, and external hospitalizations only	(3) Add all base characteristics only	(4) Add base fixed effects only	(5) Add parental controls and base characteristics only	(6) Add parental controls, base characteristics and base fixed effects	(7) Basic regression, sample with no missing variables	(8) External hospitalizations used as dependent variable, all controls
Ages 0 to 1								
CO	-0.01	-0.009	-0.016	0.005	-0.011	0	-0.012	0
	[0.014]	[0.012]	[0.014]	[0.018]	[0.013]	[0.019]	[0.013]	[0.005]
PM10	0	0	0	0.001	0	0	0	0
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]
SO_2	-1.402**	-1.950***	1.323	-0.256	1.438	0.459	-1.296**	-0.416
	[0.596]	[0.579]	[1.267]	[1.651]	[1.194]	[1.575]	[0.612]	[0.569]
NO_2	0.829**	0.916**	0.578	1.249	0.211	-0.265	0.794**	0.062
	[0.399]	[0.385]	[0.693]	[1.091]	[0.661]	[1.341]	[0.392]	[0.327]
O_3	0.07	0.085	0.061	-0.149	0.083	-0.215	0.035	0.056
	[0.250]	[0.183]	[0.197]	[0.326]	[0.233]	[0.287]	[0.213]	[0.096]
Observations	46851	44663	46851	46851	44663	44663	44663	44663
R-squared	0.37	0.38	0.37	0.37	0.38	0.38	0.37	0.31
Ages 2 to 5								
CO	0.003	0.002	0.006	0.011*	0.002	0.008	0.002	-0.002
	[0.006]	[0.005]	[0.004]	[0.006]	[0.004]	[0.006]	[0.005]	[0.004]
PM10	-0.000**	-0.000**	-0.000*	0	-0.000*	0	-0.000**	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SO_2	-0.275	-0.266	-0.245	-0.005	-0.217	0.198	-0.236	0.179
	[0.248]	[0.249]	[0.333]	[0.625]	[0.364]	[0.544]	[0.247]	[0.343]
NO_2	0.11	0.12	0.109	0.453	0.158	0.093	0.112	0.057
	[0.101]	[0.098]	[0.134]	[0.418]	[0.128]	[0.300]	[0.097]	[0.186]
O_3	0.192***	0.166**	0.270***	0.248**	0.225***	0.244**	0.163**	-0.034
	[0.071]	[0.073]	[0.077]	[0.098]	[0.077]	[0.100]	[0.074]	[0.062]
Observations	118560	114612	118560	118560	114612	114612	114612	114612
R-squared	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.26

Basic regression controls for age dummies, female dummy, race dummy and pmos*rank*year interactions as well as rain, temperature and temperature squared. Father/sponsor's controls include number of months since last enlistment, total active months in the military, age, college degree, number of dependents, enlisted in the last five years, and a dummy for whether mother was hospitalized for pregnancy. Base characteristics include distance to closest city, distance to closest city with 50,000 inhabitants, distance to closest city with 100,000 inhabitants, distance to MTF, dummies for whether closest monitor is within 30 miles, number of sponsors at the base, percent of sponsors that requested base for relocation, Pb, percent officer, percent stepchildren, average number of months in service, average number of dependents, mean ages of sponsors at base, mean age of children at base, percent White non-Hispanic at base, percent of sponsors with some college, percent enlisted within the last 5 years, percent gone in the next year, percent of children hospitalized for external causes. Standard errors (in parenthesis) are clustered at the base level. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: specification checks

Dependent variable: Child hospitalized last year for respiratory condition (=1)	(1) Basic	(2) Basic model. Add dummies for distance to monitor>30 miles	(3) Basic model. Interact pollution and distance dummies	(4) All controls (individual controls, base controls, base fe)	(5) All controls. Drop year 89	(6) All controls. Drop year 90	(7) All controls. Drop year 91	(8) All controls. Drop year 92	(9) All controls. Drop year 93	(10) All controls. Drop year 94	(11) All controls. Drop year 95	(12) All controls. Dropped 1st and 99th percentiles	(13) All controls. Drop if pollutant value > 90th percentile
Ages 0 to 1													
CO	-0.01	-0.018	-0.019	0	0.007	-0.001	0	-0.004	0.005	-0.002	-0.013	-0.007	0.032
	[0.014]	[0.012]	[0.012]	[0.019]	[0.019]	[0.020]	[0.023]	[0.022]	[0.023]	[0.020]	[0.029]	[0.023]	[0.028]
PM10	0	0	0	0	0	0.001	0	0	0	0	0.001	0	0.001
	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
SO_2	-1.402**	1.264	1.413	0.459	0.719	0.543	-0.378	0.959	0.871	-0.474	0.105	0.186	-4.55
	[0.596]	[1.069]	[1.034]	[1.575]	[1.863]	[1.716]	[1.404]	[2.280]	[1.905]	[1.689]	[2.217]	[2.006]	[2.911]
NO_2	0.829**	0.07	0.109	-0.265	0.043	-0.301	1.031	1.552	-1.187	-0.453	-1.113	0.297	-0.467
	[0.399]	[0.480]	[0.465]	[1.341]	[1.874]	[1.612]	[1.181]	[1.317]	[1.245]	[1.204]	[1.439]	[1.510]	[1.606]
O_3	0.07	-0.202	-0.037	-0.215	-0.209	0.216	0.113	-0.602	-0.27	-0.363	-0.219	0.385	1.728
	[0.250]	[0.204]	[0.195]	[0.287]	[0.370]	[0.530]	[0.234]	[0.372]	[0.357]	[0.305]	[0.282]	[0.701]	[1.050]
Obs	46851	46851	46851	44663	38630	40872	39497	35307	37474	37511	38687	39057	30401
R2	0.37	0.37	0.37	0.38	0.39	0.37	0.39	0.4	0.36	0.39	0.39	0.39	0.41
Ages 2 to 5													
CO	0.003	0.003	0.003	0.008	0.005	0.009	0.009	0.007	0.007	0.01	0.003	0.009	0.014*
	[0.006]	[0.004]	[0.004]	[0.006]	[0.007]	[0.006]	[0.005]	[0.007]	[0.007]	[0.007]	[0.008]	[0.008]	[0.008]
PM10	-0.000**	-0.000**	-0.000**	0	0	0	0	0	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SO_2	-0.275	-0.375	-0.363	0.198	0.132	0.357	-0.041	0.498	0.224	0.044	-0.077	0.492	-0.451
	[0.248]	[0.351]	[0.383]	[0.544]	[0.679]	[0.569]	[0.570]	[0.679]	[0.513]	[0.646]	[0.623]	[0.769]	[0.679]
NO_2	0.11	0.044	0.057	0.093	0.171	0.031	0.065	0.406	0.082	0.197	-0.424	0.05	0.187
	[0.101]	[0.152]	[0.147]	[0.300]	[0.301]	[0.349]	[0.336]	[0.378]	[0.328]	[0.399]	[0.356]	[0.447]	[0.241]
O_3	0.192***	0.204***	0.247***	0.244**	0.22	0.322**	0.305***	0.273***	0.210*	0.183*	0.238**	0.299*	0.337
	[0.071]	[0.076]	[0.083]	[0.100]	[0.140]	[0.153]	[0.106]	[0.104]	[0.111]	[0.094]	[0.109]	[0.175]	[0.233]
Obs	118560	118560	118560	114612	95318	102407	102206	95814	96116	97004	98807	100466	79114
R-2	0.28	0.28	0.28	0.28	0.3	0.27	0.29	0.28	0.27	0.29	0.29	0.29	0.32

See notes in Table 4. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Comparing results from alternative predictions

Dependent variable: Child hospitalized in last year for respiratory condition (=1)	Monitors within 50 miles for all pollutants[1]		Monitors within 30 miles for all pollutants		Monitors within 15 miles for all pollutants		At least one monitor in county for all pollutants	
	All at once	One at a time	IDW 30	(co) Kriging	IDW15	(co) Kriging	County weighted average	(co) Kriging
Ages 0 to 1								
CO	-0.01	-0.009	0.006	-0.008	3.3	-0.014	-0.039	0
	[0.014]	[0.011]	[0.018]	[0.020]	[2.418]	[0.066]	[0.581]	[0.027]
PM10	0	0	-0.001	0	-5.628	0.004	-0.26	0
	[0.001]	[0.001]	[0.001]	[0.001]	[4.905]	[0.004]	[1.037]	[0.000]
SO_2	-1.402**	-0.303	2.723**	2.027	1.981	-2.193	1.508	2.167
	[0.596]	[0.775]	[1.214]	[1.707]	[8.248]	[10.145]	[1.704]	[1.738]
NO_2	0.829**	0.492	-0.644	-0.144	0	-0.151	-0.001	0.656
	[0.399]	[0.413]	[0.901]	[0.945]	[0.004]	[4.127]	[0.001]	[1.286]
O_3	0.07	0.151	0.366	0.144	0.068	0.736	0.006	0.141
	[0.250]	[0.234]	[0.487]	[0.295]	[0.088]	[1.654]	[0.018]	[0.261]
Observations	46851	46851	25609	25609	4251	4251	21392	21392
R-squared	0.37		0.43	0.43	0.66	0.66	0.42	0.42
Ages 2 to 5								
CO	0.003	0	0.005	0.005	-0.105	0.020**	0.049	-0.001
	[0.006]	[0.005]	[0.006]	[0.007]	[0.678]	[0.009]	[0.103]	[0.004]
PM10	-0.000**	0	-0.001***	-0.001**	-0.447	0	-0.157	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.901]	[0.001]	[0.295]	[0.000]
SO_2	-0.275	-0.155	0.46	0.262	3.109	3.2	0.285	-0.028
	[0.248]	[0.198]	[0.374]	[0.544]	[3.033]	[4.104]	[0.312]	[0.387]
NO_2	0.11	0.077	0.016	0.146	0	-1.167	0	0.397*
	[0.101]	[0.096]	[0.253]	[0.261]	[0.001]	[1.052]	[0.000]	[0.219]
O_3	0.192***	0.131*	0.239*	0.239***	0.001	0.587	0.002	-0.019
	[0.071]	[0.067]	[0.133]	[0.080]	[0.010]	[0.548]	[0.003]	[0.116]
Observations	118560	118560	66762	66762	12431	12431	49351	49351
R-squared	0.28		0.35	0.35	0.56	0.56	0.35	0.35

(1) the sample includes bases for which the closest monitor for each of the 5 pollutants is within 50 miles of the base.
All models include basic controls as described in the notes for Table 4.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Functional form test: checking for significant interactions

	interactions and higher order terms				interactions only				higher order terms only				
	5 level	4 level	3 level	2 level	5 level	4 level	3 level	2 level	5 level	4 level	3 level	2 level	1 level
Panel A: Ages 2-5													
All controls, full sample (N=114,612)													
Adjusted R2	0.0343	0.0343	0.0343	0.0344	0.0343	0.0343	0.0344	0.0344	0.0344	0.0344	0.0344	0.0344	0.0344
AIC	-225540.10	-225490.40	-225509.00	-225515.40	-225535.30	-225498.90	-225505.40	-225527.20	-225549.40	-225522.30	-225520.40	-225527.10	-225548.70
BIC	-224642.70	-224371.10	-224544.10	-224618.00	-224705.50	-224495.40	-224559.80	-224707.00	-224816.10	-224692.50	-224709.90	-224755.10	-224892.50
P-value for test of joint significance													
all pollution terms	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0062	0.0226	0.0673
all higher order terms	0.0000	0.0000	0.0150	0.0178	0.0000	0.0009	0.0597	0.0497	0.0002	0.1077	0.8977	0.7544	0.0673
highest order terms	0.1782	0.0003	0.7988	0.0178	0.4575	0.1247	0.6875	0.0497	0.0130	0.0846	0.6763	0.7544	0.0673
All controls, drop high outliers (N=79,114)													
Adjusted R2	0.0411	0.0411	0.0412	0.0414	0.0413	0.0413	0.0413	0.0414	0.0414	0.0414	0.0415	0.0415	0.0415
AIC	-158905.20	-158764.90	-158753.50	-158741.00	-158879.10	-158762.50	-158743.10	-158737.90	-158790.80	-158748.50	-158738.60	-158734.20	-158728.30
BIC	-158432.00	-157660.70	-157630.80	-157599.70	-158340.90	-157695.50	-157601.90	-157596.60	-157872.30	-157635.00	-157588.00	-157583.60	-157577.80
P-value for test of joint significance													
all pollution terms	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0020	0.0031	0.0000	0.0000	0.0001	0.0019	0.4601
all higher order terms	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0096	0.0012	0.0044	0.0001	0.0000	0.0022	0.4601
highest order terms	0.0890	0.3080	0.3192	0.0000	0.0338	0.3864	0.1021	0.0012	0.3462	0.5066	0.1539	0.0022	0.4601
Panel B: Ages 0-1													
All controls, full sample (N=44,663)													
Adjusted R2	0.0144	0.0145	0.0146	0.0147	0.0145	0.0146	0.0147	0.0147	0.0143	0.0143	0.0144	0.0145	0.0143
AIC	-55536.87	-55505.41	-55498.21	-55476.85	-55503.67	-55491.42	-55486.05	-55465.68	-55467.83	-55463.46	-55458.75	-55451.64	-55430.57
BIC	-54674.89	-54521.53	-54523.04	-54492.97	-54598.16	-54533.66	-54510.88	-54481.80	-54501.37	-54496.99	-54492.28	-54476.47	-54437.99
P-values for test of joint significance													
all pollution terms	0.0000	0.0000	0.0000	0.0012	0.0000	0.0000	0.0010	0.0215	0.0000	0.0000	0.0030	0.0132	0.9542
all higher order terms	0.0000	0.0000	0.0000	0.0003	0.0000	0.0000	0.0004	0.0270	0.0000	0.0002	0.0009	0.0016	0.9542
highest order terms	0.5996	0.4230	0.5951	0.0003	0.6340	0.9535	0.2454	0.0270	0.3346	0.2585	0.2324	0.0016	0.9542
All controls, drop high outliers (N=30,401)													
Adjusted R2	0.0137	0.0138	0.0139	0.0137	0.0140	0.0139	0.0140	0.0137	0.0142	0.0143	0.0140	0.0139	0.0139
AIC	-38234.72	-38177.34	-38145.45	-38114.89	-38184.37	-38141.55	-38136.86	-38109.31	-38260.07	-38143.98	-38116.50	-38105.86	-38097.69
BIC	-37810.29	-37519.89	-37413.09	-37382.54	-37618.45	-37425.84	-37421.15	-37385.28	-38052.01	-37453.23	-37384.15	-37373.51	-37373.65
P-values for test of joint significance													
all pollution terms	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	0.0000	0.0351	0.2151
all higher order terms	0.0000	0.0000	0.0000	0.0426	0.0000	0.0000	0.0000	0.1023	0.0000	0.0000	0.0035	0.0338	0.2151
highest order terms	0.1285	0.6282	0.0002	0.0426	0.0521	0.4491	0.0001	0.1023	0.9737	0.0061	0.0637	0.0338	0.2151

Yellow: best fit (lowest AIC, BIC; highest adjusted r-squared); green: second best fit (second lowest AIC, BIC, second highest adjusted r-squared).

Table 8: Interpreting the results from multi-pollutant models, children ages 2 to 5
Policy exercise

	Model controls	Obs	Mean	Std. Dev.
Panel A: Linear model, full sample				
actual hospitalizations		114612	0.0115	0.1067
70th percentile and above for all pollutants				
actual hospitalizations		3147	0.0140	0.1174
predicted hospitalizations, at mean X	all controls	3147	0.0178	0.0010
	basic controls	3147	0.0114	0.0010
30th percentile and below for all pollutants				
actual hospitalizations		567	0.0071	0.0838
predicted hospitalizations, at mean X	all controls	567	0.0040	0.0002
	basic controls	567	0.0105	0.0007
Panel B: Non-linear models, dropping outliers				
actual hospitalizations		79114	0.0116	0.1073
70th percentile and below for all pollutants				
actual hospitalizations		749	0.0147	0.1204
predicted hospitalizations, at mean X	all controls	749	0.0297	0.0003
	basic controls	749	0.0129	0.0001
30th percentile and below for all pollutants				
actual hospitalizations		567	0.0071	0.0838
predicted hospitalizations, at mean X	all controls	567	0.0066	0.0006
	basic controls	567	0.0077	0.0005

Predictions made at the mean of all other explanatory variables.
See notes in Table 4 for a description of the sample and of the variables included as controls. Non-linear models include higher order terms and interactions up to 5 levels.

Table 9: Results by SES, Children ages 2 to 5

Dependent variable: Child hospitalized last year for respiratory condition	All	Non-white	White	High school or less	Some college or more	Low rank	High rank
Mean of dependent variable		0.012	0.011	0.012	0.011	0.011	0.012
Panel A: basic controls							
CO	0.002	-0.005	0.005	0.004	-0.006	0.001	0.001
	[0.005]	[0.005]	[0.008]	[0.005]	[0.019]	[0.006]	[0.007]
PM10	-0.000**	-0.001**	0	-0.000**	0	0	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
SO_2	-0.236	0.229	-0.56	-0.203	-1.578*	0.255	-1.076**
	[0.247]	[0.297]	[0.363]	[0.244]	[0.841]	[0.385]	[0.448]
NO_2	0.112	-0.027	0.241*	0.098	0.146	0.185	0.071
	[0.097]	[0.143]	[0.139]	[0.098]	[0.372]	[0.118]	[0.169]
O_3	0.163**	0.199**	0.144	0.145*	0.565*	0.006	0.359***
	[0.074]	[0.091]	[0.150]	[0.085]	[0.308]	[0.077]	[0.137]
Observations	114612	47184	67428	100377	14235	63460	51152
R-squared	0.28	0.37	0.33	0.27	0.61	0.2	0.37
P-value, F-test of significance							
All interactions with Xs		0.000		0.000		0.000	
All interactions with Xs, except pollution		0.034		0.003		0.062	
Interactions with pollutants only		0.001		0.195		0.001	
CO interaction		0.117		0.143		0.999	
PM10 interaction		0.673		0.529		0.271	
O_3 interaction		0.881		0.634		0.017	
NO_2 interaction		0.001		0.757		0.594	
SO_2 interaction		0.012		0.920		0.042	
Panel B: All controls							
CO	0.008	-0.006	0.014	0.007	-0.026	0.016**	-0.001
	[0.006]	[0.010]	[0.008]	[0.006]	[0.035]	[0.006]	[0.011]
PM10	0	0	0	0	0	0.000*	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.001]
SO_2	0.202	-0.115	0.954	0.214	-0.307	-0.489	1.352
	[0.544]	[1.142]	[0.757]	[0.633]	[2.192]	[0.887]	[0.927]
NO_2	0.081	0.194	0.027	0.038	-1.088	-0.104	0.118
	[0.297]	[0.630]	[0.404]	[0.292]	[1.944]	[0.459]	[0.812]
O_3	0.244**	0.095	0.374	0.310***	-0.092	0.017	0.556***
	[0.100]	[0.100]	[0.265]	[0.115]	[0.499]	[0.118]	[0.171]
Observations	114612	47184	67428	100377	14235	63460	51152
R-squared	0.28	0.38	0.33	0.28	0.62	0.21	0.38
P-value, F-test of significance							
All interactions with Xs		0.000		0.000		0.000	
All interactions with Xs, except pollution		0.000		0.000		0.000	
Interactions with pollutants only		0.487		0.852		0.001	
CO interaction		0.227		0.638		0.150	
PM10 interaction		0.381		0.660		0.165	
O_3 interaction		0.930		0.261		0.002	
NO_2 interaction		0.674		0.876		0.839	
SO_2 interaction		0.880		0.795		0.230	

See notes in Table 4.
* significant at 10%; ** significant at 5%; *** significant at 1%