The Needs of the Army

Using Compulsory Relocation in the Military to Estimate the Effect of Air Pollutants on Children's Health

Adriana Lleras-Muney

ABSTRACT

Recent research suggests that pollution has a 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 respiratory hospitalizations. I use individual-level data of military families and their dependents, matched at the zip code level with pollution data, for the period 1989–95. I find that for military children only ozone appears to have an adverse effect on health, although not for infants.

I. Introduction

One of the major justifications for pollution control is its potential effect on population health. The Clean Air Act states that its purpose is "to protect and enhance the quality of the Nation's air resources so as to promote the public

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health and welfare and the productive capacity of its population."[1] But pollution reductions are costly, thus for regulatory purposes it is important to determine the marginal external costs associated with polluting activities. Recent research suggests that pollution has a very large impact on asthma and other respiratory and cardiovascular conditions (WHO 2003). But there is still much uncertainty about the magnitude of these effects. Using conventional data sets, it is difficult to separate the effects of pollution on health from the effects of socioeconomic background and of other characteristics of the areas where individuals live. Polluting factories locate in areas where land is cheap and constituents have low political leverage. High-pollution areas often have higher crime rates, fewer public services, and different average socioeconomic characteristics. In addition, estimates of the effects of pollution can be biased because of sorting: Poor and disadvantaged families often live in polluted areas whereas wealthier (and healthier) families can afford to move to cleaner areas. On the other hand, individuals 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 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, occurring every 24 to 48 months, and they affect all enlisted personnel and their families: about one-third of army families experience a Permanent Change of Station (PCS) in a given year. The military claims that within rank and occupation, all members are equally likely to be relocated to a particular base. If so, families are moved to high or low-pollution areas in a manner that is independent from their socioeconomic characteristics. I test the validity of this claim in various ways, and then use this unusual characteristic of Army families to obtain estimates of the effect of various pollutants on children's health. I find that for military children only ozone appears to have an adverse effect on health, measured by respiratory hospitalizations. The effect is large: One standard deviation in O_3 increases the probability of a respiratory hospitalization by about 8–23 percent.

Even if individuals were randomly assigned across locations, various characteristics of their environment other than pollution would be affected. Another important advantage of looking at military families is that, because they generally live on military bases, their living conditions remain relatively constant from base to base. Bases provide many services, including childcare, school, entertainment, and healthcare (I discuss this in more detail below). Thus the variation in the environment (aside from weather and pollution) 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. Nevertheless, I perform several robustness checks to account for this possibility, including controlling for observed characteristics, adding base fixed effects, adding family fixed effects, and looking at the effects of pollution on hospitalizations for external causes. The results suggest omitted location characteristics are not problematic.

1. Text available at http://www.epa.gov/oar/caa/caa.txt, accessed September 22, 2006.

There are other benefits to studying the effects of pollution using the military. First, there is no reason to suspect that the effects of pollution are different for military children than those for children in the general population. Second, all enlisted personnel and their dependents are covered by military health insurance (Champus/Tricare), which is quite generous (no premiums, low deductibles), and is highly rated by its members.[2] Therefore, issues of access to care are not first-order concerns. Lastly, the data obtained from multiple administrative offices are very detailed and allow me to control for many potential confounders.

I focus on children because they are of particular interest. Lifetime (cumulative) exposure to pollution is close to contemporaneous exposure for young children—as children age, this is less true. Perhaps for this reason, children are suspected to be more susceptible than adults to pollution. Pollution is believed to cause various respiratory diseases and to aggravate existing respiratory conditions (for example, ozone and particulate matter are believed to precipitate asthma attacks).[3] Respiratory diseases are the most common diseases among children and their economic costs are believed to be large,[4] especially because they are likely to be experienced over a lifetime. Another advantage of focusing on young children is that their environment is less disrupted as a result of relocation, since they are not in school yet and most mothers of children younger than five in the military are at home.[5]

There is a vast literature in epidemiology that documents strong correlations between pollution and mortality (for example, Pope et al. 2002; Samet et al. 2000), and between pollution and other health measures, including hospitalizations (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.[6] The identification strategy used in this paper uses cross-sectional and time-series variation in pollution induced by relocations, 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 most likely also lead to reductions in income and employment).

Another is that families may move as a result of high-pollution levels, especially if they suffer from respiratory problems. Although both studies (Chay and Green-

2. In 1995, 70 percent of spouses reported being satisfied with the Army Medical System. See footnote 9 for copay information.
3. Links to description of the sources and possible health consequences of each pollutant are found at: http://www.epa.gov/air/urbanair/6poll.html
4. The four most prevalent chronic conditions among children younger than age 17 are asthma, hay fever, sinusitis, and bronchitis—see http://www.agingsociety.org/agingsociety/pdf/chronic.pdf, accessed September 22, 2005. The CDC reports that "The estimated cost of treating asthma in those younger than 18 years of age is $3.2 billion per year." See http://www.cdc.gov/asthma/children.htm, accessed September 23, 2005.
5. In 1999, about 64 percent of nonenlisted spouses with children younger than five reported being at home, retired, or unemployed. These numbers were likely to be even higher during the period under study. Information provided by West Point using data from the 1999 Survey of Active Duty Personnel.
6. See also Jayachandran (2005).

stone 2003; Currie and Neidell 2005) attempt to address the issue of omitted variable biases, neither addresses the issue of sorting. If, for example, sick individuals avoid polluted areas, this would mitigate the effect of pollution. Previous research indicates that avoidance behavior is important (for example, see Neidell 2009, or Neidell and Moretti 2008) and that individuals who experience health-related effects of pollution are more responsive than healthier individuals (Bresnahan, Dickie, and Gerking 1997). Coffey (2003) is the only study that specifically looks at the extent to which unhealthy households sort into areas with better air quality. He finds that there is indeed a substantial amount of sorting and his results suggest that sorting has a large impact on estimates of the effect of pollution on infant mortality. The design in this paper overcomes this sorting problem. In addition, this paper looks at hospitalizations, which are a more frequent event than deaths.

This paper has a few limitations. Because I relate hospitalizations to annual pollution means, the effects here could be understated. The estimates here also can be downward biased because individuals avoid pollution, for example, by staying indoors (Neidell 2009).

There are a number of additional contributions. I include measures for five major pollutants in the United States and find that models that look at the effects of a single pollutant at a time can be misleading. I use 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 positioned generally in locations where pollution is suspected to be high. I find evidence that measurement error in pollution predictions is not classical and that it has large effects on the estimated coefficients.

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 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. They contain annual individual-level information on enlisted married men and their dependents for the period 1988–98, including the characteristics of the enlisted men (age, race, education, occupation, rank, location, date of first enlistment, date of last enlistment, total number of months of active service[7]) and information on all hospitalizations (by condition) of their wives and children. Individuals' location is given by the zip code to which their sponsor (the

7. The data do not contain individual earnings, but contain almost all the variables that determine earnings, namely rank, experience, family structure, and location. Other unknown sources of household income (deployment compensation, performance bonuses, or spousal earnings) are small relative to household income.

enlisted father) 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 31. (See section A of the Appendix available at www.econ.ucla/alleras).

B. Dependents' health data

Military personnel and their dependents have access to care through two separate systems.[8] Military Treatment Facilities (MTFs) provide free care to all beneficiaries, subject to capacity. Military families also obtain care through their health insurance known as Champus/Tricare. Under Champus (Civilian Health and Medical Program of the Uniformed Services), beneficiaries paid no premiums and were all subject to a single plan.[9] Starting in 1995 a new system known as Tricare was phased in, replacing Champus.

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 percent of military dependents. Figure 1 shows the locations of all the military installations (most of which are bases) and MTFs for the Continental United States in 1990. Each circle represents an installation (the size of the circle is proportional to the number of observations) and each triangle represents an MTF.

Health data are obtained from the administrative claims filed by these two separate sources: MTFs and insurance. MTFs only filed claims for hospitalizations (no other services obtained at MTFs are observed).[10] Champus/Tricare claims exist for hospitalizations and for other services. Unfortunately Champus hospitalization claims do not report the diagnosis for the hospitalization (but most hospitalizations occur at MTFs—see below).

I construct several individual outcome measures using these claims. The first measure is whether or not the person was hospitalized[11] during the year (regardless of whether the hospitalization occurred in a military or private facility). Individuals with no hospitalization claims are assigned a zero. The second is whether the person was hospitalized in an MTF. For MTF hospitalizations only, I construct indicators for whether a hospitalization was for a respiratory condition (ICD9 codes 460 to 519, 769–770 and 786), an external cause (ICD9 800–999 or starting with "E"), or for any other cause. Births are not counted as hospitalizations. Infant mortality (or

8. Description and statistics come from Hosek et al. (1995) 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."

9. The plan included small annual individual- and family-level deductibles ($100 per family if below E4 grade, $300 otherwise), a 25 percent co-pay for outpatient costs, and a $1,000 family stop loss. There was a daily nominal inpatient cost (not exceeding $25 annually in 1994).

10. Starting in 1996 the data from MTFs are no longer available. Because claims are reported in fiscal years (which begin in October), the data for MTF hospitalizations in 1995 is missing a quarter of that year's hospitalizations, which would have been reported in 1996. Because of these changes, the data for 1995 are to be treated with caution.

11. In all cases, a hospitalization occurs if the individual was admitted to the hospital and stayed overnight.

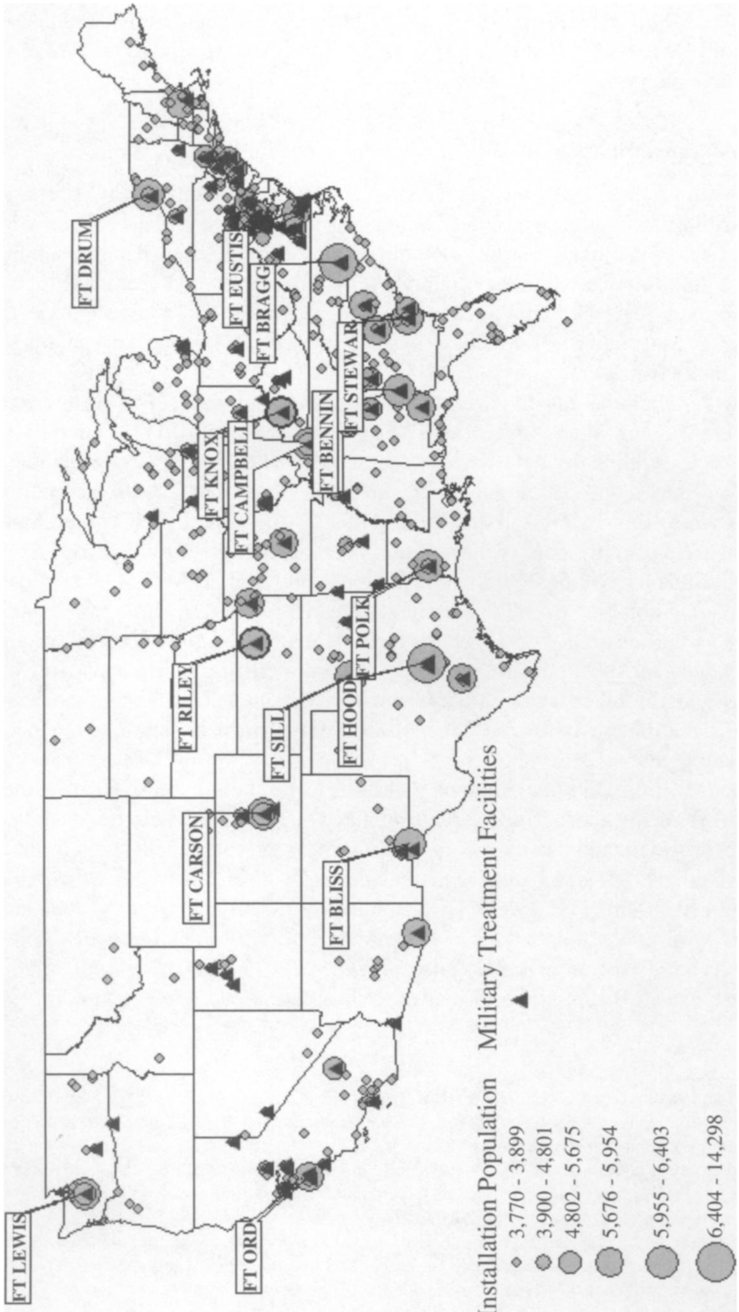

Figure 1
Distribution of military installations and military treatment facilities in 1990
Base sizes calculated from sample provided by DMDC (includes all dependents, including dependents of officers and stepchildren).

other health outcomes) cannot be constructed. Because hospitalizations are free, changes in income are unlikely to affect hospitalization rates.

C. Pollution and weather data

Pollution data come from the Environmental Protection Agency (EPA). They contain annual statistics for the period 1988–98 of measurements at the monitor level of the six major environmental pollutants in the United States, namely: particulate matter of ten micrometers in diameter (PM10), ozone (O_3), lead (Pb), carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). Only monitors that appear in at least eight years out of 11 are kept, and the missing values were interpolated within monitors over the years to obtain a balanced panel of monitors.[12] The final number of monitors is reported in Section D of the Appendix available at www.econ.ucla/alleras.

Weather data (temperature, humidity and rain) from the National Climatic Center were also merged. For zip codes without measurements, temperature and rain were predicted in the same fashion as pollution (see next section and Section B of the Appendix, available at www.econ.ucla/alleras). Weather conditions are important potential confounders. For example, very hot weather during the summer raises O_3 levels and also may result in more deaths. Weather also clearly changes with location. For this reason, I use both annual and quarterly measures to test the sensitivity of the results to detailed weather controls.

D. Assignment of pollution levels to individuals

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 average of pollution across monitors within a given radius, using the inverse of the distance to the point as weights (as in Currie and Neidell 2005). Another simple option is to calculate county averages by averaging values across monitors in a given county (as in Chay and Greenstone 2003). Alternatively one can use Kriging. Kriging consists of estimating the parameters that describe the spatial correlation between observations and then using the estimates to find predictions that minimize the sum of squared errors.[13] Kriging predictions are based on the annual

12. The data provided by the EPA contain an unbalanced panel of monitors for each pollutant. In calculating pollution levels for any given area, the addition and deletion of monitors are problematic if 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.

13. All of these methods assume that distance from monitors is an important predictor of the level of pollution (namely 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's G). The results of these tests for 1988 are available from the author upon request. In all cases the data strongly reject the hypothesis of no spatial correlation, providing support for the methods used here.

arithmetic mean at each monitor. The details of this method are given in Cressie (1993). Covariates may be used as well (in which case the method is referred to as co-Kriging) if there are other variables that are known to predict levels of pollution. These include annual measures of weather (rain, temperature, humidity, and wind direction), terrain (altitude), and emission sources (which are not available for this period and therefore not included). Today there are more sophisticated methods to map emissions into ambient concentration, using emission sources, topography, weather and other variables (for example, see Bayer, Keohane, and Timmins 2006) but the necessary data to estimate these models is unavailable for the period under study.[14]

Kriging has several advantages over the alternative methods previously used by economists (Cressie 1993). First, Kriging is the best linear unbiased predictor. Second, measures of fit of standard errors of the predictions can be obtained. Third, covariates can be used to improve the predictions. Lastly, Kriging allows prediction for a much larger number of locations in the United States compared to IDW or county averages.[15]

Research in geoscience suggests that Kriging methods are superior to deterministic methods theoretically and specifically for predicting pollution in the United States (Zimmerman et al. 1999, Anselin and Gallo 2006, Phillips et al 1997, and Hopkins et al. 1999). For example, Zimmerman et al. (1999) find using simulation methods that "Kriging methods were substantially superior to the inverse distance weighting methods over all levels of surface type, sampling pattern, noise, and correlation." Kriging is also the methodology employed by the EPA to predict ozone and PM. They report that, "Support for these methods [specifically Kriging] has emerged from scientists and state/local/EPA agencies in recent workshops" (EPA 2004). Because of these advantages Kriging predictions are used for the main results.

Maps for the Kriging predictions for each pollutant for 1990 (see Section C of the Appendix available at www.econ.ucla/alleras) show that 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, except for O_3. There is a significant amount of variation in pollution levels across the country, and this variation is different for each pollutant. Note that the predictions for Pb are poor (see Section D of the Appendix, available at www.econ.ucla/alleras).

I also match individuals to pollution levels computed using IDW (for both 15- and 30-mile radii) and using county-level averages (where the weights are number of observations at each monitor in a given year). In all cases, individuals are matched

14. Additionally, these models are highly dependent on various assumptions and none is widely accepted in environmental sciences. For example, see Tong and Mauzerall (2006).

15. Section B of the Appendix available at www.econ.ucla/alleras contains the details of the models that were used to generate Kriging predictions, and Section D of the same appendix shows the measures of goodness of fit for each pollutant and for every year.

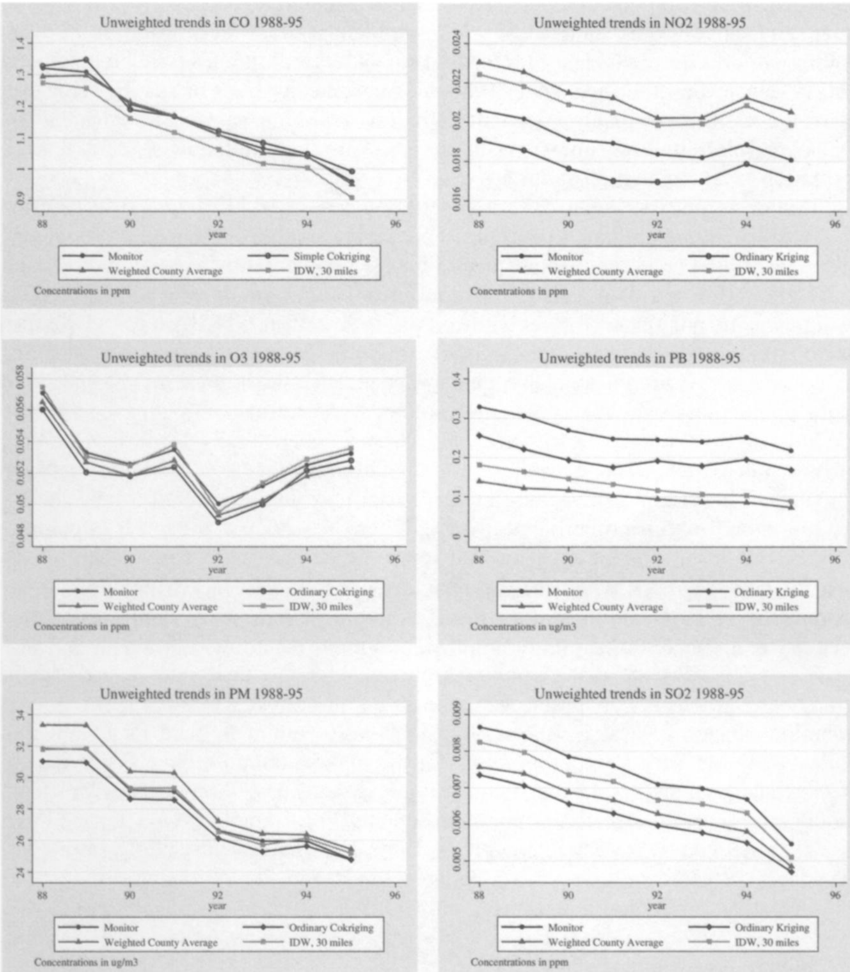

Figure 2
Comparing trends from different prediction methods

to the predictions in the zip code to which their sponsor is assigned to duty. Figure 2 shows national trends (averages across zip codes) for all pollutants from 1988 to 1995 obtained using the various methods. All prediction methods yield trends that closely follow the trends obtained from monitor data. 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, even given excellent predictions of outdoor pollution levels at the zip code level, because individuals move around quite a bit. This problem is less likely to be an issue for young children in the military (compared to adults or children in the civilian population) since they live and go to school/daycare at the base or nearby. However, personal exposure will also depend on indoor pollution as well as on individual behavior (mobility and time spent outdoors). This is a limitation of using ambient pollution levels, which most studies use.[16]

Because military installations are generally located in rural (low density) 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 aged 18 and younger 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 younger in my data. Section E of the Appendix available at www.econ.ucla/alleras 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 half of a standard deviation) except for NO_2.[17] Different levels of pollution exposure should not be of concern so long as the model used here to identify the effects of pollution on health is properly specified and there is overlap in the levels of pollution to which both groups are exposed. However, in the presence of nonlinearities (for which there is some evidence) the results may not easily be extrapolated to the population at large, limiting the external validity of this study (although external validity is a concern of most studies cited in the introduction as well.)

Figure 3 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 also has 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 1 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.[18]

E. Sample and summary statistics

The hospitalization data show that about 11 percent of children were hospitalized at least once in the previous year. This hospitalization rate is higher than that observed for children of civilian parents but similar to what has been reported elsewhere for dependents of military personnel.[19] Most of these hospitalizations occur at an MTF.

16. Neidell (forthcoming) shows individuals respond to pollution alerts, biasing coefficients of the effects of ozone on health.

17. Section F of the Appendix available at www.econ.ucla/alleras shows the trends in exposure for both populations, which are also quite similar.

18. This has been observed in previous studies as well (for example, Samet et al. 2000). I also examined whether there is evidence of multicollinearity but found none.

19. In the NHIS during the same years, the number is approximately 6 percent for children aged 0–5 of families with annual incomes below $40,000. Hospitalization rates are higher for the military because of

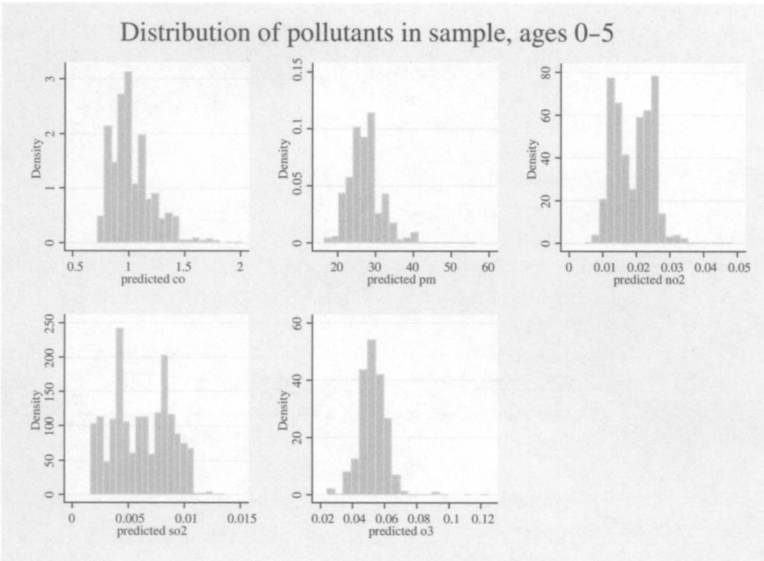

Figure 3

Table 1
Correlations between pollutants using Kriging estimates at the base

	CO	PM10	NO_2	SO_2	O_3
Across bases					
(N = 935 base*year observations)					
CO	1				
PM10	0.5303	1			
NO_2	0.5106	0.3998	1		
SO_2	0.0821	0.0684	0.2414	1	
O_3	−0.0208	0.228	0.1447	0.3593	1
In sample					
(weighted by population in base N = 159,275)					
CO	1				
PM10	0.5494	1			
NO_2	0.1982	0.089	1		
SO_2	0.2727	0.3377	0.4165	1	
O_3	−0.0307	0.1438	0.1438	0.2723	1

These correlations are based on spatial predictions using Kriging and thus might be quite different in reality. But since monitors for different pollutants do not overlap, the real correlations at particular locations are not known.

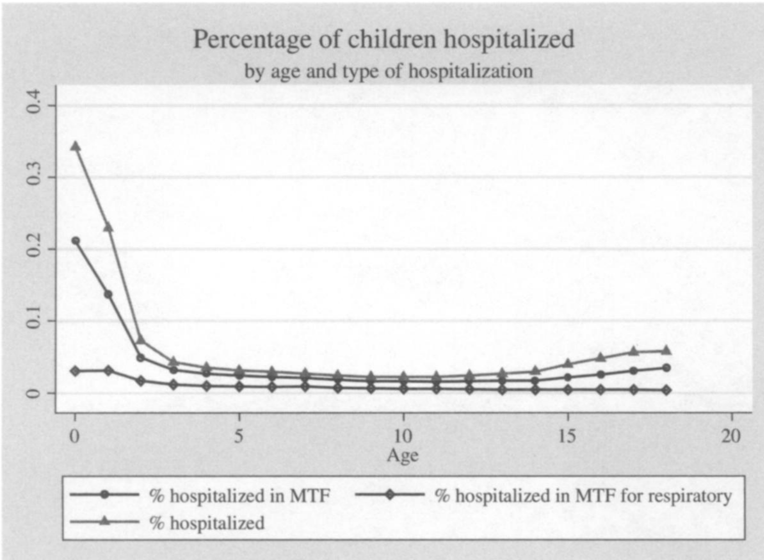

Figure 4

Among MTF hospitalizations (for which diagnosis codes are known), 26 percent are due to respiratory conditions. Figures 4 and 5 show the distribution of hospitalizations for all ages. Hospitalization rates fall rapidly with age, bottoming out between aged five and 15, after which they start rising. Because hospitalization rates are so low for older children and since young children are more susceptible to the immediate effects of pollution, I limit the analysis to children younger than age five (but I test the robustness of the results to including other ages). Figure 5 suggests that children aged 0–1 exhibit a much larger rate of respiratory hospitalizations than children aged 2–5, so I analyze the effects of pollution separately for these two age groups.[20]

The sample includes observations from 1989 to 1995. There are no claims data from MTFs from 1996 forward. As DMDC recommended, the year 1988 is dropped because the health insurance claims data for that year appear to be incomplete. To minimize differences in access to care, individuals with no access to a military

differences in demographic characteristics and because of the very generous insurance provided by the military. Hosek et al. (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 percent higher than those of civilians in fee-for-service plans." They report that percentage of dependents that were hospitalized overnight was about 8.5 percent in the early 1990s (Table B.5) and adjusting for covariates it is about 11.3 percent (Table 3).

20. In other data, the main difference in hospitalization is between infants and others. In my sample age is observed as of December 31st of the year. Many children that are one year of age and were hospitalized within the last year may have been infants at the time of the hospitalization.

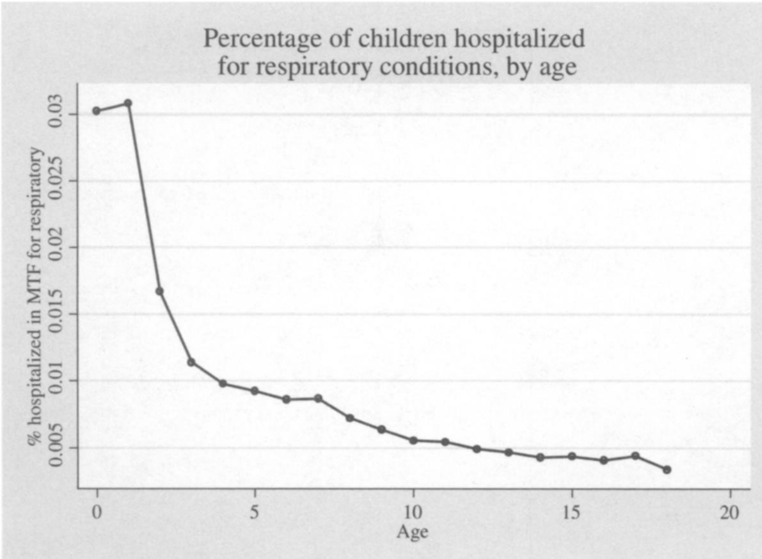

Figure 5

hospital are excluded. 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 (I discuss this in more detail below). Individuals with missing explanatory variables were also dropped. The final sample includes 67,582 married enlisted men and 94,113 children. It includes roughly 3 percent of the Army any given year, and somewhat less for 1990 and 1991 because of deployments for the Gulf War (only children whose fathers are stationed in the continental United States are included).[21]

Table 2a shows the summary statistics for the sample. About half of the children are male, and 60 percent are white non-Hispanic. On average, children can be followed for 3.2 years (if no distance to monitor restriction is made). Of those who are observed in consecutive years, about 30 percent 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 on active duty for about nine years and have between two and three dependents (including their spouse); 12 percent have at least some college education. For those observed in two consecutive years,

21. For example, in 1989, there were a total of 769,741 military personnel in the Army (see http://web1.whs.osd.mil/mmid/mmidhome.htm). The number of married men with dependents stationed in the continental United States, for which I was given data for 1989 included 305,706. The final number of enlisted men in the sample that year is exactly 20,779, about 2.7 percent of the Army.

Table 2a
Summary Statistics for Children aged 0–5

Variable	Children 0–5 (N = 159,275) Mean	Standard Deviation	Children 0–1 (N = 44,663) Mean	Standard Deviation	Children 2–5 (N = 114,612) Mean	Standard Deviation
Children's characteristics						
Year	92.094	1.987	92.192	1.908	92.056	2.016
Male = 1	0.51	0.5	0.511	0.5	0.509	0.5
Age	2.671	1.607	0.632	0.482	3.466	1.116
White, non-Hispanic = 1	0.6	0.49	0.63	0.483	0.588	0.492
Number of years observed in sample	3.187	1.601	2.493	1.369	3.458	1.604
Moved in year = 1 (observed consecutively)	0.291	0.454	0.236	0.425	0.3	0.458
Moved in year = 1 (not observed consecutively)	0.317	0.465	0.24	0.427	0.329	0.47
Gone next year = 1	0.259	0.438	0.272	0.445	0.254	0.435
Hospitalized at least once during year	0.102	0.302	0.248	0.432	0.045	0.207
Hospitalized in MTF	0.063	0.242	0.138	0.345	0.033	0.179
Hospitalized in MTF for respiratory condition	0.016	0.126	0.028	0.165	0.012	0.107
Hospitalized in MTF for external cause	0.004	0.06	0.003	0.058	0.004	0.06
Hospitalized in MTF for nonrespiratory condition	0.046	0.209	0.112	0.315	0.02	0.139

Father and mother characteristics						
Number of dependents (including wife)	2.43	1.204	2.227	1.174	2.51	1.206
Some college or higher	0.118	0.323	0.102	0.303	0.124	0.33
Father's age	29.259	5.283	27.566	5.241	29.919	5.151
Mother hospitalized at least once during year	0.202	0.401	0.362	0.481	0.139	0.346
Mother hospitalized in MTF	0.138	0.345	0.244	0.429	0.096	0.295
Mother hospitalized in MTF for pregnancy-related	0.108	0.31	0.223	0.416	0.063	0.242
Total active military service in months	106.497	61.969	87.629	60.435	113.85	60.996
Number of months since reenlistment	30.03	26.618	27.038	24.307	31.196	27.378
In the military fewer than six years = 1	0.249	0.433	0.385	0.487	0.196	0.397
Increased rank (observed consecutively) = 1	0.188	0.391	0.227	0.419	0.174	0.379
Increased education (observed consecutively) = 1	0.021	0.143	0.019	0.136	0.022	0.145

Sample: children aged 0–5 of married men enlisted in the army and stationed in the Continental United States 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.

about 2 percent increase their education and about 19 percent move up in rank. For reference, the table also shows statistics separately by age.

Table 2b shows the characteristics that are common in 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 935 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 percent of the sample has county predictions for all pollutants; 5 percent has IDW15 predictions for all pollutants, and IDW30 predictions exist for about 50 percent 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 one-third of all military personnel make a permanent change of station (PCS). In a 20-year career, individuals are relocated an average of 12 times.[22] Most soldiers move their families as well: According to the 1987 Survey of Army families, 92 percent of the responding spouses said they were living in the same location as their spouse; in 1995, the percentage was 87.5 (Croan et al. 1992).

In principle, the army uses rank and military occupation (PMOS) in combination with "needs of the Army" to determine relocation. 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 PMOS 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."

The military unit responsible for relocation (previously known as Perscom) uses an automated system that produces target numbers by PMOS, 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 also is determined by these factors, 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. In practice enlisted personnel are generally not assigned to their preferred location. Among those surveyed in 1987, only 35 percent reported that they were assigned to their preferred location (Burnam et al. 1992). Moreover these num-

22. Source: Relocation Assistance Conference, Dallas 2003.

Table 2b
Summary Statistics for base level characteristics

Variable	Ages 0–5 Mean	Ages 0–5 Standard Deviation	Ages 0–1 Mean	Ages 0–1 Standard Deviation	Ages 2–5 Mean	Ages 2–5 Standard Deviation
Base characteristics						
Temperature (F)	35.199	13.681	34.174	13.526	35.598	13.721
Rain (inches)	56.332	5.650	56.396	5.761	56.307	5.606
Number of fathers at base	6178.2	4488.9	6547.3	4543	6034.4	4459.4
Percent of enlisted personnel requesting this base	2.875	2.708	3.064	2.762	2.802	2.683
Distance to closest city (miles)	3.686	4.400	3.756	4.510	3.658	4.355
Distance to closest city with pop 50K (miles)	14.058	11.992	14.183	12.035	14.009	11.975
Distance to closest city with pop 100K (miles)	19.240	19.224	19.482	19.523	19.146	19.105
Distance to MTF (miles)	0.056	0.112	0.056	0.110	0.056	0.112
Pollution average annual mean						
Carbon monoxide (CO) (ppm)	1.028	0.187	1.018	0.182	1.032	0.188
Nitrogen dioxide (NO_2) (ppm)	0.019	0.006	0.019	0.006	0.019	0.006
Ozone (O_3) (ppm)	0.053	0.008	0.052	0.008	0.053	0.008
Lead (Pb) (ug/m3)	0.097	0.125	0.096	0.124	0.098	0.126
PM10 (particles with diameter $\leq$ 10 micrometers) (ug/m3)	27.237	4.175	26.979	4.003	27.338	4.236
Sulfur dioxide (SO_2) (ppm)	0.006	0.003	0.006	0.003	0.006	0.003
Monitor information						
Percent with county predictions for all pollutants	0.184	0.388	0.192	0.394	0.181	0.385
Percent with IDW15 predictions for all pollutants	0.052	0.222	0.046	0.210	0.055	0.227
Percent with IDW30 predictions for all pollutants	0.496	0.500	0.487	0.500	0.499	0.500

(*continued*)

Table 2b (*continued*)

Variable	Ages 0–5 Mean	Ages 0–5 Standard Deviation	Ages 0–1 Mean	Ages 0–1 Standard Deviation	Ages 2–5 Mean	Ages 2–5 Standard Deviation
Average characteristics at base (from largest possible sample, includes children of all ages)						
Percent officers at base	0.179	0.152	0.171	0.143	0.182	0.155
Percent stepchildren at base	0.105	0.026	0.106	0.024	0.104	0.026
Average total active months in service at base	155.47	18.53	154.27	17.81	155.93	18.78
Average number of dependents at base	2.817	0.128	2.820	0.121	2.816	0.131
Average dad age at base	34.202	1.767	34.102	1.692	34.241	1.793
Average children age at base	8.809	0.957	8.732	0.938	8.839	0.962
Percent white at base	0.625	0.094	0.622	0.092	0.626	0.094
Percent college at base	0.311	0.158	0.303	0.150	0.314	0.160
Percent newly enlisted at base	0.112	0.054	0.117	0.052	0.111	0.054
Percent gone next year at base	0.269	0.101	0.265	0.097	0.271	0.103
Percent children hospitalized at base	0.058	0.017	0.058	0.017	0.058	0.017
Percent children hospitalized at MTF at base	0.037	0.016	0.038	0.016	0.036	0.016
Percent children hospitalized at MTF at base for respiratory condition	0.010	0.005	0.010	0.005	0.010	0.005
Percent children hospitalized at MTF at base for external causes	0.004	0.002	0.004	0.002	0.004	0.002
N	159,275		44,663		114,612	
Number of children	94,113		36,552		71,683	
Number of sponsors	67,582		32,309		54,756	
Number of bases	177		142		175	

Notes: ug/m^3 stands for micrograms per cubic meter; ppm stands for parts per million. Sample: children aged 0–5 of married men enlisted in the army and stationed in the continental United States 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.

bers overestimate the amount of choice. Individuals learn (and the Army encourages them) to "play the system" by submitting preferences for locations where their skills are needed and where they can further develop their career.[23] Thus the choices soldiers list are constrained; for example, if an individual is due for an overseas transfer, he is unlikely to list a U.S. base among his choices, even if he does not want to go overseas.

This evidence is consistent with the idea that most individuals have very little choice over their relocations and that, within rank and occupation, assignment is not related to other individual characteristics of the enlisted personnel. Some individuals may nevertheless have more control over their relocations than others. According to Croan et al. (1992), junior ranking soldiers have the least control over where and when they move (also see Segal 1986). Because of this evidence I drop officers from my sample and focus on lower ranked soldiers. For this paper it is particularly important to know if relocations are correlated with family health, in particular children's health. The army to some extent does consider family health needs in relocation assignments through the Exceptional Family Member Program (EFMP). The EFMP program is designed to be an assignment consideration and not an assignment limitation.[24] EFMP only results in assignments to locations where needs can be met if available, not to relocations that soldiers prefer. Of particular interest for this study is the fact that EFMP is not granted because of "Climatic conditions or a geographical area adversely affecting a family member's health, [even if] the problem is of a recurring nature."[25]

To further support the empirical strategy in this paper, I provide statistical evidence that individual characteristics observed at the time of relocation are uncorrelated to base of relocation or to pollution levels at the new base. First, using the sample of individuals that are observed in different locations in two consecutive years, I estimate N equations of the form:

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

These are linear probability models that predict the location of individual i in year $t+1$ based on individual characteristics X in year t (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.[26] The error terms are clustered at the sponsor level since a sponsor can have several children and they may be observed in several years. There are as many equations as bases to which individuals are relocated. Among those who move

23. See regulation AR 614–200 3.3.

24. Governing regulation AR 608–75, dated May 1996.

25. 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.

26. 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.

between t and $t+1$, no other observed characteristics other than rank and occupation in year t should predict location in year $t+1$. For each regression, I perform a joint test that $\beta=0$. If, indeed, individual characteristics are orthogonal to location, then the vast majority of the tests should not reject the null.

In Table 3a, I present the distribution of the p-values for these tests. In Panel A, I look at relocations to all bases (excluding foreign bases) from all bases for parents of children aged 0–5. In order to maximize the sample size for this test I do not drop individuals without access to MTFs or those in bases far from pollution monitors. Only in 6.6 percent of the regressions are individual characteristics predictive of relocation. If I include foreign bases this becomes 10.6 percent. Thus, at the 10 percent level we cannot reject the hypothesis that relocations are uncorrelated with observable characteristics beyond occupation and rank for relocations within the United States. In Panel B, I use only individuals included in the estimation sample, altogether or broken by age groups. Whether or not I include relocation to foreign bases, at the 5 percent level we cannot reject the hypotheses that individual characteristics are orthogonal to location.[27]

This evidence suggests that for the vast majority of enlisted personnel, relocations are not chosen. A weaker but relevant test is whether personal characteristics (in particular health or SES) predict pollution at relocation bases. For example, are high SES sponsors more likely to request bases that have low-pollution levels? This would appear not to be the case. 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, 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.) A priori this anecdotal evidence suggests that even if individuals were able to choose their location, it is not clear how their characteristics would be correlated to pollution. But to test this in the data I estimate the following equations:

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

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 in year t, 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 base level. For each equation I test whether the Xs are jointly significant, and also whether the health variables are jointly significant. The results are presented in Table 3b. In Panel A, I use the largest sample of 0–5-year-olds that moves bases. In Panel B, I present results for those in the estimation sample who moved. In all cases, the test does not reject the null that the Xs are not significant. Hospitalizations in year t are also not significant predictors of pollution in year $t+1$ among movers.

27. Ideally, one would allow for the error term to be correlated across equations, but STATA will not estimate SUR or multinomial logits with a large number of equations/choices.

Table 3a
Testing whether individual and family characteristics at time t *predict location at time* t + 1*, conditional on rank and occupation interactions. Sample: Children aged 0–5 who moved*

Variable	Sample	Number of bases	Mean	Standard Deviation	Number of bases	Mean	Standard Deviation
Panel A **Children aged 0–5 regardless of location in continental United States who moved**							
	to any base, excluding foreign				to any base, including foreign		
One equation per year and base, control for rank*pmos $D = 1$ if $p < 0.05$	ages 0–5	380	0.066	0.248	386	0.106	0.309

(*continued*)

Table 3a (*continued*)

Variable	Sample	Number of bases	Mean	Standard Deviation	Number of bases	Mean	Standard Deviation
Panel B							
Children aged 0–5 in estimation sample who moved (restrict to bases close to monitors and military hospitals)							
	to any base, excluding foreign				to any base, including foreign		
One equation per year and base, control for rank*pmos $D=1$ if $p<0.05$	ages 0–5	265	0.000	0.000	271	0.018	0.135
One equation per year and base, control for rank*pmos $D=1$ if $p<0.05$	ages 0–1	160	0.000	0.000	166	0.006	0.078
One equation per year and base, control for rank*pmos $D=1$ if $p<0.05$	ages 2–5	243	0.000	0.000	249	0.008	0.089

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-related).

Table 3b
Testing whether individual and family characteristics at time t *predict pollution levels at time* t + 1*. Sample: Children aged 0–5 who moved. P-values reported*

	CO	PM10	SO_2	NO_2	O_3
Panel A					
children aged 0–5 regardless of location in continental United States who moved (to continental U.S. base)					
Test all variables = 0	0.667	0.414	0.836	0.340	0.433
Test health variables = 0	0.580	0.624	0.351	0.654	0.703
Panel B					
Children aged 0–5 in estimation sample who moved (restrict to bases close to monitors and military hospitals)					
Aged 0–5					
Test all variables = 0	0.451	0.092	0.784	0.581	0.695
Test health variables = 0	0.132	0.310	0.891	0.832	0.652
Aged 0–1					
Test all variables = 0	0.481	0.523	0.858	0.132	0.493
Test health variables = 0	0.672	0.283	0.546	0.392	0.557
Aged 2–5					
Test all variables = 0	0.975	0.245	0.468	0.891	0.788
Test health variables = 0	0.744	0.757	0.333	0.371	0.619

Linear regression models. Errors clustered at the base level. Individual and family characteristics 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-related). The table tests whether all the individual and family explanatory variables (with the exception of the rank*occupation*year interactions) are jointly significant using an F-test.

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 various city sizes) and also obtained aggregate statistics on the frequency with which bases are listed as individuals' top choices for 1991–95 from West Point. These measures can be used as proxies for unpopularity in the regressions of interest (see below).

IV. Main results

A. Empirical approach

For each age group (aged 0–1 and 2–5), I estimate the following individual-level linear probability model,[28]

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

where the dependent variable *Hosp* is a dummy variable indicating whether or not child i living in base b was hospitalized in year t 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, which always includes base fixed effects to minimize concerns of location-specific time invariant omitted variables. Because weather is a potential confounder, rain, temperature, and temperature-squared are included in all models. The main results in the paper include individual measures of pollution, rather than constructing an index for pollution because (a) pollutants are regulated individually, and therefore it is important to know the externalities associated with each; (b) it is not theoretically clear how to create and interpret such an index (see Greene 1997 for a discussion); and (c) there are potentially interactions between pollutants. However, in the next section I also report results using various indexes.

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. Unbiased estimates can be obtained under the assumption that, conditional on the included covariates, there are not unobserved individual- or base-level characteristics that predict respiratory hospitalizations and are correlated with pollution.

If location is indeed not chosen and pollution is uncorrelated to own characteristics, then cross-sectional estimates of the effects of pollution will be unbiased. Adding individual characteristics or family fixed effects 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).

In principle, one of the advantages of the military is that their lifestyle will remain relatively stable as they move across the country. Relocations are not systematically associated with promotions. The military adjusts compensation for differences in the cost of living across location (Title 37 Chapter 7 Section 403b United States code). Its insurance program during this period did not charge differential prices by location. The Army provides housing in several bases. It also attempts to guarantee the availability of a number of services across all military bases, both to enlisted personnel and their families, including counseling, relocation assistance, fitness facilities, libraries and recreation centers, among others. It is difficult to ascertain the extent to which the number and quality of these programs vary across locations.[29]

28. Results from logits are similar to those presented here.
29. Buddin (1998) reports that "a base-level survey is planned to collect information on base program activities and expenditures along with information about the base community." This information is thus not available for the 1989–95 period.

But according to some, "the Army replicates the same plans at each base and does not take local conditions under consideration" (Way-Smith et al 1994, quoted in Buddin 1998).

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. In addition to base fixed effects, I add controls for a number of base- and year-level characteristics, 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 also is included as a base level control, although the predictions for lead are fairly poor. Because weather is an important confounder that varies across bases and potentially affects health and pollution levels, I repeat estimation using quarterly rather than annual weather measures.

The specifications used here relate annual pollution measures to annual hospitalization measures. Thus they measure the effects of pollution that occur within a relatively short period of time. However, previous studies have found effects of pollution within a year and even for much shorter windows (daily or weekly).[30] On the other hand, the effects of pollution may be lagged or even cumulative over the years—these cannot be estimated here.

In all estimations the errors are clustered at the base level, since all individuals in the same base are exposed to the same levels of predicted pollution, which are measured with error and are likely to be correlated over time within bases (Bertrand et al. 2004).[31]

B. Main results

The results from estimating Equation 3 for each age group are presented in Tables 4a and 4b. All specifications include rank*occupation*year dummies. The first column shows the effects of pollution when only age, gender, race, annual weather measures (temperature and rain), and base fixed effects are controlled for. The results for ages 0–1 show no significant effects, regardless of the specification in Table 4a. The pollutants are also insignificant when tested jointly (*p*-values for the test of joint significance are reported at the bottom of the table). I do not discuss results for this group in what follows.

The pattern is different for children aged 2–5. For them there appears to be a significant positive effect of O_3. Column 2 adds all parental controls and a dummy for whether the child was hospitalized for an external cause. Again there is a significant positive effect of O_3 for children aged 2–5 similar in magnitude to that in Column 1. This is consistent with previous results that individual characteristics are uncorrelated with pollution levels at the base. Next, I examine the effect of base-

30. Chay and Greenstone (2003) relate annual infant mortality to annual pollution measures; Currie and Neidell (2005) look at mortality and pollution within a week; studies in epidemiology have commonly related daily mortality to levels of PM10 (for example, Samet et al. 2000).

31. Standard errors would also need to be corrected because pollution levels are predicted. However I do not implement any correction here since the effect of measurement error is likely to be larger anyway.

Table 4a
Effect of pollutants on respiratory hospitalizations, main results, children aged 0–1

Dependent variable: Child hospitalized last year for a respiratory condition (= 1)	(1) Basic controls	(2) Parental controls + external hosp	(3) Add base characteristics	(4) Use quarterly measures of rain and temperature	(5) Family fixed effects	(6) Movers (Family fixed effects)	(7) Nonmovers (Family fixed effects)
Base FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental controls and external hosp	No	Yes	Yes	Yes	Yes	Yes	Yes
Base characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Weather	Annual	Annual	Annual	Quarterly	Quarterly	Quarterly	Quarterly
Family FE	No	No	No	No	Yes	Yes	Yes

CO	0.005	0.001	0	−0.009	0.034	0.173	0.013
	[0.016]	[0.016]	[0.019]	[0.023]	[0.072]	[0.206]	[0.076]
PM10 (*100)	0.064	0.039	0.04	0.056	−0.153	0.247	−0.205
	[0.082]	[0.078]	[0.090]	[0.083]	[0.208]	[1.243]	[0.235]
SO_2	0.087	0.542	0.46	−1.049	−1.549	6.06	1.034
	[1.537]	[1.352]	[1.571]	[1.709]	[5.629]	[19.006]	[6.236]
NO_2	1.087	0.42	−0.266	0.384	0.941	−3.38	1.539
	[1.119]	[1.162]	[1.344]	[1.253]	[3.639]	[23.619]	[4.138]
O_3	−0.162	−0.182	−0.215	−0.141	−0.441	−0.186	−0.417
	[0.320]	[0.335]	[0.288]	[0.296]	[0.791]	[3.329]	[0.915]
Observations	44,663	44,663	44,663	44,663	44,663	5,971	38,692
R-squared	0.37	0.38	0.38	0.38	0.73	0.93	0.74
p-value (joint significance of 5 pollutants)	0.414	0.8593	0.9543	0.9544	0.879	0.9476	0.9283

Basic regression controls for age dummies, female dummy, race dummy and pmos*rank*year interactions as well as rain, temperature and temperature squared. Family 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-related. 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 five 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 percent; ** significant at 5 percent; *** significant at 1 percent.

Table 4b
Effect of pollutants on respiratory hospitalizations, main results, children aged 2–5

Dependent variable: Child hospitalized last year for a respiratory condition (= 1)	(1) Basic controls	(2) Parental controls and external hospitalizations	(3) Add base characteristics	(4) Use quarterly measures of rain and temperature	(5) Family fixed effects	(6) Movers (Family fixed effects)	(7) Nonmovers (Family fixed effects)
Base fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental controls and external hosp	No	Yes	Yes	Yes	Yes	Yes	Yes
Base characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Weather	Annual	Annual	Annual	Quarterly	Quarterly	Quarterly	Quarterly
Family fixed effects	No	No	No	No	Yes	Yes	Yes

CO	0.007	0.007	0.008	0.002	0.024**	0.006	0.025*
	[0.006]	[0.006]	[0.006]	[0.008]	[0.011]	[0.037]	[0.013]
PM10 (*100)	0.008	0.007	0.014	0.026	−0.007	0.139	−0.001
	[0.023]	[0.023]	[0.021]	[0.029]	[0.047]	[0.149]	[0.048]
SO_2	0.299	0.315	0.202	0.271	0.239	0.492	0.089
	[0.566]	[0.560]	[0.544]	[0.492]	[1.117]	[2.607]	[1.163]
NO_2	0.32	0.318	0.081	−0.055	−0.353	−1.958	0.185
	[0.385]	[0.381]	[0.297]	[0.357]	[0.567]	[1.220]	[0.729]
O_3	0.203*	0.200*	0.244**	0.207**	0.350**	0.129	0.351**
	[0.104]	[0.104]	[0.100]	[0.104]	[0.154]	[0.624]	[0.172]
Observations	114,612	114,612	114,612	114,612	114,612	21,428	93,184
R-squared	0.28	0.28	0.28	0.28	0.5	0.72	0.53
p-value (joint significance of five pollutants)	0.2174	0.2214	0.0717	0.2177	0.0118	0.6444	0.0146

Basic regression controls for age dummies, female dummy, race dummy, and pmos*rank*year interactions as well as rain, temperature and temperature squared. Family 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-related. 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 five years, percent gone in the next year, percent of children hospitalized for external causes. Standard errors (in parentheses) are clustered at the base level.

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

level controls. Column 3 adds all base characteristics in addition to individual characteristics, and in Column 4, I replace annual weather measures with quarterly measures. The effect of O_3 is positive and significant and remains around 0.2. All other coefficients remain insignificant.

In Column 5, I add family fixed effects. Pollution effects in this specification are identified by changes in pollution over time for those that remain in a given base, and due to changes in pollution associated with relocation for those that move. O_3 remains positive and significant, although somewhat larger in magnitude. Interestingly, in these specifications CO is significant and larger than previously estimated.

In Columns 6 and 7, I separate movers and nonmovers. For movers, the effects are identified from changes in pollution across bases only. The effect of O_3 is not significant and it is somewhat smaller, but not statistically different from the previous estimates. No coefficient is in fact significant in this specification, although it is worth noting that the sample size is greatly diminished. The results for nonmovers are very similar to those using the full sample: Both CO and O_3 are positive and significant. It is perhaps surprising that the coefficients for movers are smaller than those for nonmovers. However, the mover sample uses observations before and after a move is observed. But the same individuals appear in the nonmover sample in those years when they do not move. So the samples contain the same individuals, but in different years. Since everyone is moved eventually, there is no one in the sample that is really a nonmover. Thus these results suggest that the effects of pollution are cumulative and thus are not observed in the short run (by definition in the mover sample exposure is short-possibly around six months, depending on the distribution of moves within calendar year, which is not known).

Across specifications, it also is worth noting that although insignificant, the effect of SO_2 is always positive and relatively stable. The coefficient on NO_2 is very unstable, and the effect of PM10 is also not very robust.

The results suggest that there are no statistically significant effects of pollution for children aged 0–1 on respiratory hospitalizations, and that O_3 (and perhaps CO but no other pollutant) significantly increases the probability of a respiratory hospitalization for children aged 2–5. Why would O_3 affect only older 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."[32] Outdoor exposure most likely explains why there are no significant effects of O_3 for children aged 0–1, since they are much less likely to play and exercise outdoors. These results are consistent with McConnell et al. (2002) who find that children that play sports and spend time outdoors are more likely to develop asthma only in areas with high ozone levels. In terms of magnitude the coefficient on O_3, which ranges from 0.13 to 0.35, implies that an increase of one standard deviation in O_3 (0.008, 15 percent relative to the mean) increases the probability of a respiratory hospitalization by 0.0010–0.0028 percentage points, or about 8–23 percent,

32. See http://www.epa.gov/airnow/ozone-bw.pdf

relative to the mean for children aged 2–5 (0.012). The implied elasticity ranges from 0.5 to 1.5.

C. Specification checks and other estimation issues

Table 5 shows a number of additional specification checks for children aged 2–5 with all controls and quarterly weather and family fixed effects (as Column 5 of Table 4b). The first column reproduces the results from the previous table. In Column 2 and 3, I test the sensitivity of the results to using different age groups. Column 2 presents results pooling together all children aged 0–5. These results are very similar to those presented for children aged 2–5. Although as children age, they—like adults—may be less responsive to immediate changes in pollution, the age cutoff I chose for the main results is somewhat arbitrary. Thus, Column 3 present results for children aged 2–6 (results are similar but somewhat smaller if I include age seven as well). The effects of O_3 are robust to these changes, generally significant and fluctuating between 0.1 and 0.3. The results for CO are qualitatively similar.

Columns 4 and 5 test the sensitivity of the results to pollution outliers in the data. In Column 4, I drop observations where the value of any pollutant exceeds its 99th percentile or is below its first percentile. Figure 3 suggests that higher values rather than lower values of pollution may be problematic, so Column 5 drops all observations where the value of the pollutant exceeds its 95th percentile for every pollutant. The results are somewhat sensitive to outliers. All the coefficients are insignificant, although both sample size and variation in pollution are diminished in these regressions. The effect of CO falls and is insignificant. The coefficient on O_3 is not significant, and varies a lot in magnitude. These results suggest that outliers matter.

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. In both panels, all of the coefficients for individual pollutants are statistically insignificant. They are also jointly insignificant.[33]

Table 6 compares the results obtained from different prediction methods and from limiting the sample based on distance to monitor. Again I present results only for children aged 2–5, with and without family fixed effects. The first column reproduces the results in Table 4b. 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. The effect of O_3 remains significant and is very similar whether it is entered alone or with other pollutants—perhaps this is to be expected since it is not strongly correlated with other pollutants. CO is also not very sensitive to adding other pollutants. But the effects of PM10, NO_2, and SO_2 are quite sensitive to addition of other pollutants, even though these are insignificant.

Finally, I compare the results using Kriging to those obtained using inferior prediction methods used in previous research. In the next two columns I present the

33. The p-values for the children aged 0–1 and 2–5 are 0.9724 and 0.6350 respectively.

Table 5
Specification checks. Family fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Aged 2–5	Aged 0–5	Aged 2–6	Aged 2–5	Aged 2–5	Aged 2–5
Dependent variable: Child hospitalized last year for respiratory condition (=1)	Family fixed effects, all controls,and quarterly weather	Family fixed effects, all controls, and quarterly weather	Family fixed effects, all controls, and quarterly weather	Dropped 1st and 99th percentiles	Drop if pollutant value > 95th percentile	Dependent variable: Hospitalized last year for nonrespiratory cause
CO	0.024**	0.028***	0.024***	0.011	0.004	−0.003
	[0.011]	[0.011]	[0.008]	[0.013]	[0.014]	[0.016]
PM10 (*100)	−0.007	−0.021	−0.024	−0.004	0.017	−0.017
	[0.047]	[0.039]	[0.036]	[0.056]	[0.064]	[0.060]
SO_2	0.239	−0.154	0.411	0.837	0.093	0.054
	[1.117]	[0.822]	[0.951]	[1.237]	[0.899]	[1.539]
NO_2	−0.353	0.19	−0.36	−0.194	−0.432	−0.316
	[0.567]	[0.517]	[0.364]	[0.686]	[0.670]	[0.650]
O_3	0.350**	0.310**	0.305**	0.092	0.611	−0.019
	[0.154]	[0.151]	[0.123]	[0.402]	[0.440]	[0.245]
Obs	114612	159275	140666	100466	95456	114612
R-2	0.5	0.46	0.46	0.52	0.53	0.51

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

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[a]		Monitors within 30 miles for all pollutants		Monitors within 15 miles for all pollutants		At least one monitor in country for all pollutants	
	All at once	One at a time	IDW 30	(co) Kriging	IDW15	(co) Kriging	County weighted average	(co) Kriging
All controls								
CO	0.002	0.004	0.004	−0.003	0.007	−0.029	−0.003	0.009
	[0.008]	[0.008]	[0.007]	[0.013]	[0.026]	[0.030]	[0.007]	[0.014]
PM10 (*100)	0.026	0.03	−0.049*	−0.021	0.022	0.057	0.01	0.025
	[0.029]	[0.029]	[0.027]	[0.042]	[0.151]	[0.218]	[0.054]	[0.107]
SO_2	0.271	0.545	0.745	−0.005	−3.887	−2.06	−0.112	1.459
	[0.492]	[0.465]	[0.934]	[1.168]	[3.349]	[3.763]	[1.132]	[1.637]
NO_2	−0.055	−0.003	−0.345	0.043	−0.435	−0.747	−1.137***	−0.141
	[0.357]	[0.337]	[0.446]	[0.538]	[1.243]	[1.541]	[0.370]	[0.644]
O_3	0.207**	0.216**	0.072	0.182	−0.761	−0.499	−0.299	0.379
	[0.104]	[0.104]	[0.229]	[0.120]	[0.524]	[0.518]	[0.337]	[0.263]
Observations	114612		64348	64348	12103	12103	43353	43353
R-squared	0.28		0.36	0.36	0.58	0.58	0.37	0.37

(*continued*)

Table 6 (*continued*)

Dependent variable: Child hospitalized in last year for respiratory condition (= 1)	Monitors within 50 miles for all pollutants[a]		Monitors within 30 miles for all pollutants		Monitors within 15 miles for all pollutants		At least one monitor in country for all pollutants	
	All at once	One at a time	IDW 30	(co) Kriging	IDW15	(co) Kriging	County weighted average	(co) Kriging
All controls and family fixed effects								
CO	0.024**	0.025**	0	0.01	−0.017	−0.004	0.008	0.009
	[0.011]	[0.011]	[0.009]	[0.012]	[0.028]	[0.035]	[0.013]	[0.019]
PM10 (*100)	−0.007	0.006	−0.093**	−0.122**	−0.045	−0.051	−0.02	−0.039
	[0.047]	[0.051]	[0.044]	[0.061]	[0.110]	[0.218]	[0.067]	[0.088]
SO_2	0.239	0.538	2.081**	0.619	1.297	3.873	0.904	1.787
	[1.117]	[1.186]	[0.938]	[1.737]	[2.253]	[2.393]	[1.543]	[1.877]
NO_2	−0.353	−0.352	−0.929	−0.562	−1.25	−1.391	−1.000*	−0.993
	[0.567]	[0.607]	[0.604]	[0.574]	[1.077]	[1.133]	[0.503]	[0.678]
O_3	0.350**	0.367**	0.505	0.498**	0.005	−0.168	−0.482	0.097
	[0.154]	[0.153]	[0.432]	[0.215]	[0.696]	[0.548]	[0.659]	[0.363]
Observations	114,612		64,348	64,348	12,103	12,103	43,353	43,353
R-squared	0.5		0.52	0.52	0.55	0.55	0.51	0.51

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

results that compare IDW30 and Kriging using the same estimation sample (limiting the sample to only those with monitors for all pollutants within 30 miles). Kriging and IDW30 yield coefficients of about the same magnitude for O3, but they are quite different otherwise. The standard errors are also quite different. In the next two columns, I compare IDW15 and Kriging. In these specifications the size and sign of the coefficients is again different although no coefficient is significant (although the sample is now quite small). Lastly I compare Kriging to county-weighted average predictions. The rationale for these predictions is not based on spatial correlation, but rather on 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 also is not clear (and not known) that county averages 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. This exercise highlights the difficulty in estimating multipollutant models—the samples for which the effects of all pollutants can be estimated are very small, particularly in the military since many bases are in rural areas.

It is worth noting that as the distance to the monitor falls, the coefficients from Kriging estimates also change, and they do not always become larger, suggesting that the measurement error in pollution is nonclassical (although sample size also is falling). Direct evidence of nonclassical errors is presented in Section G of the Appendix, available at www.econ.ucla/alleras. For each pollutant, I plot the standard error of the Kriging predictions (divided by its mean) as a function of distance to the closest monitor in 1990. The graph shows that the standard error of the predictions gets larger as the distance to the closest monitor increases for all pollutants, but especially for NO_2, SO_2, and O_3. This measurement error is particularly large relative to the mean for NO_2 and SO_2 and smallest for O_3.

In summary, this section has shown that O_3 has a robust positive and significant effect on the probability that a child aged 2–5 is hospitalized for a respiratory condition during the year. There are no significant and robust effects of pollutants for younger children. PM10, 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. The results are sensitive to outliers.

D. 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, because it may not be physically possible to lower one pollutant while "holding all others constant." Some combinations of pollution may not be physically attainable because of the way pollutants interact with each other. For example, 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 the effect of lowering emissions of a particular pollutant.[34] It also 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 multipollutant 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 in all pollutants. This experiment lowers all levels of pollution simultaneously to combinations that are feasible (since they are observed).

The actual percentage of children hospitalized for respiratory conditions is 1.15 percent. However the percentage is higher (1.4) for those living in bases where all pollutants levels 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 with all controls, the difference between the two groups is 0.010, so moving from a high to a low-pollution area lowers predicted hospitalization by about 60 percent. With family fixed effects the reduction is even larger, about 80 percent. Since few children live in such high-pollution areas, these numbers are not informative about what the effects decline in pollution across the country on the entire population. A different exercise is to think of moving all children to low-pollution areas. This results in predicted hospitalizations of 0.0079, or about a 30 percent decline relative to the mean. This is a substantial decline.

In order to better assess the magnitude of these effects, it is interesting to compute the implied overall health effects and costs associated with pollution. I use estimates for asthma reported in Weiss et al (2000). In 1985–94, asthma resulted in 477,000 hospitalizations, 1.6 million emergency room visits and 10.8 million physician visits. Thus, assuming that moving all children in the population to low-pollution areas would also lower their hospitalizations by 30 percent, this would correspond to 143,100 fewer hospitalizations, 480,000 fewer ER visits, and 3.2 million fewer physician visits per year. These estimates assume that pollution has the same effect on morbidity than it has on hospitalizations, which is not clear—this is a limitation of the use of hospitalizations as an outcome. However, these numbers suggest that lowering pollution would result in savings of about 928 million (in 1994 dollars) in direct medical expenditures, without counting prescription drugs or activity limitation.

34. To obtain appropriate estimates of the effects on health of policies that regulate 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 at this point. See Dominici et al (2003) for a discussion.

E. Results using pollution indexes

Given the difficulty in interpreting the results using individual pollution measures as regressors, a possible alternative is to combine them all into a single measure of overall pollution. Because there is no single optimal way to combine different pollutants into a single measure from either a theoretical or statistical point of view, I construct three indexes based on commonly used procedures: principal components analysis, principal factor analysis, and simple averages. All three measures are linear combinations of standardized pollution measures, but each uses a different set of weights: Simple averages give each component the same weight, principal components chooses the weights that maximize the variance of the index, and principal factors chooses the weights that uses the most common variation across components.

Results are reported in Table 7 for the sample of older children and for two specifications: The basic specification (as in Column 1 of Table 4) and the saturated specification that includes family fixed effects and quarterly weather measures (as in Column 4 of Table 4). Panel A shows the results when the indexes are entered linearly (the weights used by each index are reported at the bottom of the table). Regardless of the choice of index and of the specification, the coefficients are positive and significant, suggesting higher values of the index increase the probability of hospitalization for a respiratory condition, although the magnitudes are larger when family fixed effects are included. The coefficients imply that a one standard deviation increase in the value of the index (reported at the bottom of the table) results in a 22–28 percent increase in hospitalizations (relative to the mean hospitalization) using the basic specification, or a 37–42 percent increase, using the saturated model. These results are in line with the exercise performed above and suggest large effects of pollution.

Results using individual pollutants suggest the pollution effects may not be linear. For example, the results are sensitive to outliers. Unreported regressions using interactions and nonlinear models also suggested that pollution effects may not be monotonic, but these were very imprecisely estimated. To explore this issue, I estimate models where the index is replaced by three dummy variables, one for each quartile of the distribution of the index, excluding the bottom quartile, which serves as the reference group. These results (Panel B) are much more sensitive to specification and to the specific index used. They are also not very precisely estimated, so it is difficult to draw conclusions from these results.

V. Conclusion and discussion

This study uses plausibly exogenous variation in pollution induced by military relocations to identify the effect of the five major air pollutants on children's respiratory hospitalizations. I find that for military children aged 2–5, only ozone (O_3) appears to have an adverse effect on health, measured by respiratory hospitalizations. These effects are large: the implied elasticity for the probability that a child is hospitalized for a respiratory condition with respect to O_3 is between 0.5 and 1.5. No other individual pollutant appears to significantly affect respiratory hospitalizations, although the results suggest CO might also increase hospitalizations.

Table 7
Effect of pollutants on respiratory hospitalizations, main results—children aged 2–5, using a single index for pollution instead of individual components

Index used:	First principal component: weighted average (of standardized components)		Simple average of standardized components		First principal factor: weighted average (of standardized components)	
Controls:	Basic	Family fixed effects and quarterly weather	Basic	Family fixed effects and quarterly weather	Basic	Family fixed effects and quarterly weather
Panel A						
Basic linear specification						
Index	0.0021**	0.0034**	0.0055**	0.0082***	0.0033**	0.0054**
	[0.0010]	[0.0013]	[0.0023]	[0.0028]	[0.0016]	[0.0025]
Observations	114612	114612	114612	114612	114612	114612
R-squared	0.282	0.501	0.282	0.501	0.282	0.501

Panel B

Nonparametric estimates (bottom quartile of index serves as reference group)

Second quartile = 1	0.0022	−0.0020	0.0037	−0.0014	0.0024	0.00056
	[0.0025]	[0.0046]	[0.0026]	[0.0047]	[0.0021]	[0.00276]
Third quartile = 1	0.0056	0.0024	0.0057*	0.0020	0.0060**	0.0065**
	[0.0036]	[0.0051]	[0.0032]	[0.0050]	[0.0029]	[0.0032]
Fourth quartile = 1	0.0062	0.0067	0.0076**	0.0056	0.0048*	0.0043
	[0.0042]	[0.0056]	[0.0038]	[0.0052]	[0.0026]	[0.0035]
Observations	114,612	114,612	114,612	114,612	114,612	114,612
R-squared	0.282	0.501	0.282	0.501	0.282	0.501

Robust standard errors in brackets. The specification with basic controls includes all the regressors in Column 1 of Table 4, and the specification with family fixed effects and quarterly weather includes all the regressors in Column 4 of Table 4. The indexes are constructed as weighted averages of the five major pollutants, after each pollutant has been standardized to have mean 0 and standard deviation of 1. The different indexes are computed as follows:
First principal component = $0.5161*PM10+0.4973*CO+0.2362*O_3+0.5296*SO_2+0.3873*NO_2$. Mean 0, standard deviation 1.41 Simple average = $(PM+CO+O_3+SO_2+NO_2)/5$. Mean 0, standard deviation 0.62 First Principal factor = $0.6294*PM10+0.6041*CO+0.2198*O_3+0.5208*SO_2+0.3966*NO_2$. Mean 0, standard deviation 0.812
* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Also I do not find any robust and significant effects for children aged zero and one, consistent with previous findings that children that exercise outdoors are at higher risk for ozone—but the small samples also may explain the absence of significant findings for this age group. Finally, I find evidence that measurement error in pollution predictions is not classical and that it has large effects on the estimated coefficients.

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 aged 2–5 hospitalized for respiratory causes by as much as 80 percent, which again suggests the effects of pollution on respiratory diseases in children are large. It is tempting to use these results to do cost benefit calculations of ozone reductions. However, this is not a straightforward exercise. Ozone is not directly emitted into the atmosphere; it is formed from reactions between NOx (nitrogen oxide), CO, and hydrocarbons. There are multiple ways to reduce ozone levels, for example, by reducing NOx emissions, but the reductions in O_3 that ensue are difficult to predict—the relationship is nonlinear and depends on a number of assumptions about weather conditions and levels of other pollutants, for example. These calculations are beyond the scope of this paper.

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 additional methodological differences (the identification strategy, the number of pollutants included and the methods used to predict pollution in space, for example) that make it difficult to ascertain the reason for the differences in the results.

This study has a few limitations. First, the only outcome analyzed is whether an overnight hospitalization occurred—for example, for asthma, there are three ER visits per hospitalization, and about 23 physician doctor visits per hospitalization. But this outcome is less extreme than mortality, so in this dimension this paper improves upon previous work in economics.

Pollutant measures are averaged over the year. Perhaps average annual pollution levels 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). Also, this study uses pollution as measured at public monitors—military bases may have their own local sources of air pollution, which may be poorly captured here.

The last issue is whether the results are representative of the effects for the population at large. 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 socioeconomic background, including, for example, generous health insurance. To the extent that the effects of pollution may differ by

SES, these differences may be important. Military children are also exposed to somewhat lower levels of pollution than the population—if the effects of pollution are nonlinear, this would affect the external validity of the estimates.

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