The Effects of Long-Term Exposure to Pollution on Health*

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Abstract: We provide the first causal evidence on how long-run exposure to fine particulate matter ($PM_{2.5}$) at contemporary ambient levels contributes to the development of chronic disease in an initially healthy population. Our analysis links detailed personnel records for roughly 150,000 U.S. Army soldiers to high-resolution annual measures of $PM_{2.5}$. Because soldiers enter service exceptionally healthy and receive uniform access to care, new diagnoses reflect pollution's physiological impact rather than preexisting conditions or differential health care access. They are also required to relocate based on the needs of the Army which provides us with quasi-random variation in initial duty-station assignments, which we use as an instrument for cumulative pollution exposure. We find that sustained $PM_{2.5}$ exposure substantially increases morbidity — particularly hypertension and related circulatory conditions — with additional effects on asthma. In contrast, short-run fluctuations in pollution have little detectable effect, underscoring the cumulative nature of pollution's health burden even though this is a healthy population exposed to pollution levels considered safe by current standards. These results demonstrate that even moderate long-run exposure can erode health capital in ways that are invisible to studies focused on short-run variations or mortality alone, and they highlight the importance of regulatory standards that account for chronic exposure risks.

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I-Introduction

Air pollution poses a persistent threat to human health worldwide. While extreme episodes of pollution receive the most attention, most individuals experience pollution as a steady, low-to-moderate exposure over many years. A growing literature documents that even short-run fluctuations in particulate matter affect health and productivity (Dominici et al. 2003; Neidell 2004; Graff Zivin and Neidell 2012; Knittel et al. 2016; Chang et al. 2016; Schlenker and Walker 2016; Deryugina et al. 2019), but far less is known about whether sustained exposure produces lasting physiological damage. Distinguishing temporary effects from cumulative harm is essential for assessing the welfare costs of pollution and the adequacy of current regulatory standards, particularly because chronic exposure is thought to influence a wide range of health conditions, many of which may manifest long before mortality. This paper provides the first causal evidence on how long-run exposure to fine particulate matter (PM2.5) impacts the onset of chronic disease.

It is very challenging to find settings in which to properly estimate the impacts of long-term exposure. Much of our evidence on the effects of long-run exposure comes from observational studies, which find that chronic pollution is associated with a wide array of adverse health outcomes (Dockery et al. 1993; Pope et al. 2002; Di et al. 2017; Beelen et al. 2014). However, it is unclear whether these estimates are causal. In the long run, people choose where to live (and thus their level of pollution exposure) based on their income, underlying health, and their preferences for local amenities (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011, Finney, Goetzke and Yoon, 2011). Moreover, households can re-optimize their locational choices in response to short-run pollution shocks, thus limiting the value of such shocks for identifying long-run effects. As a result, individuals who live in more polluted places may differ along many dimensions, and these areas may also differ not only in pollution levels but in amenities more broadly. This "endogenous sorting" of people to places generates confounding variation that obscures pollution's independent effect.

We address this challenge by exploiting a unique feature of the U.S. Army's personnel system. After completing basic training, service members are assigned to bases across the

country according to the Army's operational needs rather than soldier preferences. This institutional feature implies conditional random assignment of soldiers to locations, such that pollution exposure at the initial posting is as good as random, conditional on occupation and skill, as balance tests confirm. Although subsequent assignments may be influenced by soldiers making pollution potentially endogenous, the pollution concentration at initial assignment is strongly predictive of cumulative exposure over a soldier's career, providing a relevant and plausibly exogenous instrument for long-term pollution exposure.

Several additional aspects of this setting make it particularly well suited to studying long-run morbidity effects. First, the population we examine is exceptionally healthy at baseline: recruits are young and must pass stringent physical and medical screenings—only about 23 percent of American youth who apply to serve in the Army meet eligibility standards (Council for a Strong America 2023)—meaning that any health conditions observed during service represent new, rather than preexisting, diagnoses. Second, our focus on morbidity outcomes captures earlier stages of disease progression. Mortality-based studies necessarily miss the long period during which chronic conditions develop; by contrast, morbidity provides a more sensitive measure of pollution's impact on health and lifetime well-being. Third, Army personnel have uniform, generous access to healthcare with comprehensive administrative records, allowing us to distinguish persistent conditions from transient episodes while also controlling for the socioeconomic disparities in care-seeking that complicate civilian analyses. Finally, due to the regimented nature of military work there are limited opportunities for avoidance behavior such as avoiding outdoors activities when pollution levels are high.

We assemble a unique dataset that allows us to track long-run pollution exposure and health outcomes at an unusually fine level of detail. Using administrative Army files, we obtain personnel records for roughly 150,000 soldiers who served in the Army at least five years, along with comprehensive annual healthcare encounters for circulatory and respiratory conditions—the categories most plausibly affected by air pollution. To capture persistent illness, we measure morbidity using repeated diagnoses of the same condition, thereby

minimizing the influence of isolated or potentially miscoded episodes. Each soldier's annual duty location enables us to construct complete locational histories over their entire service career. We then merge these histories with satellite-derived $PM_{2.5}$ concentrations, which provide consistent coverage nationwide, including rural base locations that lack ground monitors.

Our results reveal significant impacts from long-term pollution exposure on soldier health. Instrumented long-run $PM_{2.5}$ exposure leads to pronounced increases in circulatory disease—particularly hypertension—with additional impacts on asthma. Short-run fluctuations in pollution, by contrast, have little detectable effect in this young and healthy population, underscoring the cumulative nature of pollution's health burden. These results are robust across specifications, alternative outcome definitions, and tests for selective attrition. Notably, naïve OLS estimates in our sample yield inconsistent and frequently counterintuitive associations between pollution and disease, underscoring how misleading observational correlations can be when sorting is not addressed.

Our analysis contributes to a nascent literature that seeks to estimate the elusive causal effects of long-run air pollution exposure. Foundational studies in China has exploited large regional differences in particulate concentrations, leveraging differential exposure to ambient particulate pollution induced by heating policies across geographic boundaries to document substantial mortality impacts (Chen et al., 2013; Ebenstein et al., 2017). In the United States, quasi-experimental studies have examined policy-driven changes in precursor pollutants or differential exposure to traffic-related pollution at fine spatial scales, again focusing largely on mortality outcomes (Anderson, 2020; Barecca et al., 2021). These papers represent important advances, but they rely on the assumption that individuals do not systematically move in response to pollution or related conditions, an assumption that is difficult to validate when exposure is defined for places rather than people. Recent work by Deryugina and Reif (2023) makes headway on this limitation by following individuals across locations and embedding quasi-experimental estimates of short-run pollution shocks into a structural model to project long-run survival effects among the elderly population.

We complement this work in three important ways. First, whereas most quasi-experimental studies identify long-run effects by exploiting shocks to ambient pollution concentrations in particular locations and therefore must assume limited selective mobility, our design leverages exogenous mobility itself. Because initial Army assignments send otherwise similar soldiers to bases with different steady-state pollution levels, we obtain quasi-random variation in long-run exposure that is tied to individuals rather than places.[1] Nonetheless, like all studies of long-run pollution exposure, our approach is not immune to concerns that pollution levels may be bundled with other location-specific characteristics that may independently influence health outcomes. Three aspects of the military setting help to limit this attribution problem. First, soldiers' employment and health care are provided directly by the Army, so local labor-market conditions and civilian health-system quality play a much smaller role than in civilian studies. Second, life on or near military bases is partly insulated from surrounding communities, reducing exposure to many local attributes that typically correlate with air quality. Moreover, the military seeks to provide similar living conditions to all soldiers, regardless of their location. Thus, while pollution levels will differ across military bases, most other amenities will not as vary much among the military as among civilians. Third, soldiers' frequent reassignments reduce their opportunities to integrate into local communities. Consistent with this, our estimates remain quite stable when we use LASSO regression to select among 70 location-specific characteristics as potential confounders.

Second, by focusing on morbidity rather than mortality, we capture earlier stages of disease progression that have significant implications for long-run welfare. While mortality is a costly outcome when it occurs, it is relatively rare and only captures the most severe health effects of pollution, and it can do so only for frail populations, typically very young children or the elderly. In contrast, morbidity is more prevalent, especially in a younger and generally healthy population, and thus provides a more sensitive measure of the pollution's cumulative physiological burden.

[1] As previously noted, Deryugina and Reif (2023) follow individuals over time, but address endogenous residential location choices by relying on a structural model to extrapolate long-run effects from short-run pollution shocks. Our approach differs by exploiting conditionally random assignment to locations.

Third, our more recent setting allows us to study sustained exposure to fine particulates at concentrations directly relevant to contemporary U.S. regulatory debates. This stands in contrast to the very high particulate levels investigated in China (Chen et al., 2013; Ebenstein et al., 2017), the elevated, traffic-adjacent pollution levels studied by Anderson (2020), and the high SO2 exposures that arise in the earlier historical periods studied in other U.S. work (Barecca et al., 2021; Deryugina and Reif, 2023).

Taken together, our findings suggest that the welfare costs of air pollution extend well beyond the short-run fluctuations traditionally emphasized in policy discussions. Even moderate long-run exposure can erode health in ways that are not captured by short-run analyses or mortality studies. By leveraging quasi-random initial assignments, following individuals over time, and focusing on cumulative morbidity outcomes, our results provide new evidence for evaluating current air-quality standards and their ability to protect long-run health and human capital. Our findings suggest that long-term exposure to pollution levels currently considered safe are in fact detrimental to health.

II- Background

A. Biological effects of pollution

There are many biological pathways by which air pollution exposure may harm health over the long term. As air pollutants enter the bloodstream, they can affect multiple organs and increase systemic inflammation (Møller et al. 2014), impair immune function (Glencross et al. 2020), and alter gene expression through epigenetic mechanisms (Alfano et al. 2018), among others, potentially causing permanent and irreversible damage. Fine particulate matter (PM2.5), for example, can penetrate deep into the lungs and translocate into circulation, contributing to oxidative stress, endothelial dysfunction, and the progression of atherosclerosis. Over time, repeated exposure may accelerate the development of chronic conditions such as cardiovascular disease, chronic obstructive pulmonary disease, and lung cancer. Sustained inflammation and cumulative biological damage imply that even modest increases in exposure, when experienced persistently, can substantially elevate long-term morbidity and mortality risks.

Short-term and long-term exposures may differ in their underlying pathophysiological consequences. Acute exposure is often associated with transient responses, such as bronchoconstriction, airway irritation, elevated blood pressure, or temporary systemic inflammation, that can trigger events like asthma exacerbations or cardiovascular episodes among vulnerable individuals (e.g., Pope and Dockery 2006). In contrast, chronic exposure reflects the accumulation of these insults over time, leading to structural and functional changes in organs, including airway remodeling, plaque formation in arteries, and persistent immune dysregulation. Thus, while short-term spikes may precipitate acute events, long-term exposure shapes disease incidence and progression by gradually altering baseline physiological function.

B. Institutional Details on the Army

Every year about 180,000 individuals apply to serve in the US Army. The Army conducts various tests of physical and mental fitness to identify individuals fit for military service. Individuals with specific health problems, such as hypertension and asthma, are not allowed to enlist. Currently, only roughly 30% of applicants are deemed eligible to serve based on these tests. Given that enlistees have a clean bill of health, any health conditions that we detect in our analysis likely reflect the initiation of the condition.

As part of this process, individuals take the Armed Forces Qualification Test (AFQT) both to assess whether an applicant is eligible to enlist and to determine the types of training they are eligible for. This test measures basic math, verbal, and reasoning skills. While not an IQ test, it assesses general aptitude and is often viewed as a rough indicator of cognitive ability important for military training and job performance.

Once an individual is deemed eligible, they complete ten weeks of basic combat training, followed by advanced training that varies in length depending on their specialization and occupation. The Army offers a wide range of choices, including combat positions (e.g., infantryman), intelligence (e.g., intelligence analyst), mechanical (e.g. helicopter repair) and medical (e.g. medic). The initial entry training phase takes between four and twelve months, at which point a soldier reports to their first operational assignment.

The location of this first assignment is determined according to Army operational needs. Each quarter the assignment office at the Army Human Resources Command (HRC), which consists of civilian personnel with military leadership, gathers information from each base on their needs for soldiers with different types of skills, akin to assessing the "labor demand" of each base. This demand is determined by various Army considerations including national defense goals, specific plans for a base, and the rotation (turnover) of existing personnel. Bases vary in their demand for specific skills based on type of operations performed at each base. For example, helicopter mechanics serve at installations that host combat aviation brigades, such as Fort Campbell or Fort Bragg. This demand also varies over time, due to changing Army priorities and can both grow (e.g. in the event of a war) or decrease (for instance if a base is scheduled to close). Thus, for a soldier specializing in a given skill in a given quarter, the locations to which they can serve are limited.

The supply of soldiers of different skills is determined by the Army's enlistment and training, and partly by soldier's preferences. At the time of enlistment, a future soldier can choose the skill they will specialize in given their AFQT and the availability of positions as determined by contracts available in a given specialty.

HRC will determine relocations each quarter to meet demand for every skill at each base given the supply of solders that quarter. All else being equal, HRC may elect to assign individuals closer to their home of record (where they enlisted from), but the bulk of assignments are determined by Army needs, which the soldier must comply with. Every time a soldier is due to move locations, soldiers can influence their assignment location by ranking up to three bases or one state of their choice. However, these preferences are not considered during the allocation of initial assignments. This forms the basis for our conditional random assignment assumption: conditional on seniority, specialization and occupation and enlistment quarter, soldiers are quasi-randomly assigned initial locations.

Soldier initial service contracts are for a duration of 2-6 years, though two is considerably less common, with the first main relocation occurring after three years of service. Soldiers are able to express their preferences for subsequent assignments although the needs of the Army are always met first. Once the initial enlistment term ends, soldiers may re-enlist for additional terms, with locational preferences more closely considered in an effort to retain their service. In fact, roughly 30% of reenlistment contracts include either stabilization or station of choice as an option. As a result, while the initial location assignment is typically beyond the control of the soldier (conditional on skills and timing), subsequent relocations are less likely to be as good as random since the Army will increasingly prioritize soldier preferences to increase retention of trained personnel.

III-Data

a. Data sources

Army personnel file: Provided by the Office of Economic and Manpower Analysis (OEMA), this dataset contains one observation per soldier and fiscal year, for every year a soldier is actively serving in the Army. The data set includes information on assignment location, demographics (age, race, sex, marital status), Armed Forces Qualification Test (AFQT) scores, educational attainment, pay grade, primary military occupational specialty (PMOS), and special qualification identifiers (SQI). PMOS defines a soldier's role and career field, while SQI is a skill identifier that designates specialized training or qualifications within a soldier's PMOS. Together PMOS and SQI determine the type of work a soldier can do and thus their location opportunities.

Health care claims data: We combine health care claims data from 2015 to 2020 across multiple sources. These come from the Comprehensive Ambulatory/Professional Encounter Record (CAPER) for Military Health System (MHS) outpatient care; the Standard Inpatient Data Record (SIDR) for MHS inpatient care; the TRICARE Encounter Data Non-Institutional (TEDNI) for TRICARE outpatient care and TRICARE Encounter Data Institutional (TEDI) for TRICARE inpatient care. These cover every single interaction that soldiers and their dependents have with health care systems. These claims include details on the diagnosis for each interaction (ICD-9 and ICD-10-CM codes).

Pollution data: We use data on fine particulate matter 2.5 micrometers or smaller ($PM_{2.5}$) at the zip code × month level. These data, provided by Van Donkelaar et al. (2021), combine satellite retrievals of aerosol optical depth, chemical transport modeling, and ground-based measurements to generate monthly estimates for 1998–2019. We overlay the satellite pollution grid with zip code polygons and compute an area-weighted average of the grid cells intersecting each ZIP code to assign exposure values. The data are deemed to be the most comprehensive granular data on pollution produced to date and allow for examination of questions that have been difficult to study in the past using pollution monitor data only (e.g. Currie et al. 2023). To align with our personnel file, we aggregate the pollution data per zip code × fiscal year and link them to personnel records using the zip code of the soldier's unit.[2]

Other data: Weather has a well-established impact on both health and pollution formation, making it an important confounder when assessing the impacts of particulate matter pollution (Graff Zivin and Neidell 2013; Neidell 2009; Crouse et al. 2015). To account for this, we merge data on temperature and precipitation with military personnel. Meteorological data come from NASA's Daymet project, which includes daily information on temperature and precipitation. We compute annual precipitation (rainfall in mm). To account for the nonlinear effects of temperature, we compute the average annual temperature, annual number of days with temperature below 32°F and annual number of days with temperature above 90°F.

We also use data from a variety of sources to obtain county-level characteristics. Economic characteristics come from county data books (ICPSR #20660) and include demographic information (e.g. population size), economic indicators (e.g. labor force participation, unemployment rates, poverty rates, and education levels), health professional shortage areas, information on public expenditures on various areas and data on crime. Information

[2] The majority of soldiers live on the base they are assigned to or nearby. Even when they reside outside the base, they spend most of their time at the base while at work so we consider the pollution at the base to be the relevant measure of exposure.

on the availability and quality of health care comes from the Dartmouth Atlas. The data are provided at the hospital referral region level and includes mortality rates among the Medicare population, Medicare reimbursement rates, and information on health care performance. Altogether, we have more than 70 variables that we can use to characterize the economic, social, and health environment in a zip code. These data are collected for the years 2000-2007 and we only use a single measure for each zip code.

b. **Primary outcomes of interest**

$PM_{2.5}$ enters the lungs and crosses into the bloodstream to impact the cardiovascular system. In their 2010 review, Brook et al. (2010) summary the medical evidence as suggesting that "Air pollutants have been linked with endothelial dysfunction and vasoconstriction, increased blood pressure (BP), prothrombotic and coagulant changes, systemic inflammatory and oxidative stress responses, autonomic imbalance and arrhythmias, and the progression of atherosclerosis." Thus, we focus our analysis primarily on circulatory outcomes, which include cardiovascular conditions.

Although $PM_{2.5}$ is primarily thought of as affecting circulatory conditions, we also consider respiratory conditions, which previous work has shown to be affected in the short run and could be aggravated in the long run. Asthma, chronic bronchitis, allergic rhinitis, COPD and lung cancer in particular are believed to be caused or aggravated by pollution (see reviews by Grigorieva and Lukyanets, 2021; Tran et al., 2023). While there is a growing literature linking $PM_{2.5}$ to other health outcomes, we focus on these first-order outcomes given the young age and healthy status of our sample.

Using the claims data, we construct separate indicators for whether an individual has a circulatory or respiratory diagnosis according to ICD-9 and ICD-10-CM codes. Circulatory codes range from 390–459 or I* and include a diverse set of conditions of various severities. Additional analyses focus on subsets of conditions that may be more likely to arise for our population: hypertension, peripheral vascular disease, coronary artery disease, and heart failure. For example, roughly 7.5% of the U.S. population aged 18-39 has hypertension, whereas <1% have congestive heart failure (Cheryl et al. 2017).

We follow a similar procedure for respiratory diagnoses, which range from 460–519 or J*. Respiratory codes also contain a wide range of conditions; we also explore impacts separately for asthma, chronic obstructive pulmonary disease, acute upper respiratory infection, and influenza and pneumonia. For example, 8% of people aged 22-39 have asthma while <2% have COPD (CDC 2021).

A key challenge in using claims data to define outcomes involves distinguishing acute health episodes from underlying chronic conditions. For example, a soldier may experience one episode of heart palpitations, which does not necessarily indicate an underlying cardiovascular condition. Since our aim is to measure morbidity, chronic health conditions are the more relevant construct. To that end, we follow previous work (Birman-Deych et al. 2005; Gershon et al. 2009) and classify a soldier as having a chronic condition if they have at least 3 claims with diagnoses for a given outcome. We also show results using a range of alternative thresholds (at least 1 to 5 claims). Thus, our health outcomes capture whether at any point in the 2015-2020 observation period, soldiers were diagnosed with a particular chronic condition.

c. Sample construction and descriptive statistics

We begin with soldiers who entered military service between 1999 and 2019, the period for which we can observe $PM_{2.5}$ exposure (N = 1,148,499). Individuals in higher pay grades and in thinly populated branches may have more influence over their location assignment because it is more difficult to replace individuals with specialized or rare skills. To avoid this issue, we restrict the sample to individuals serving in conventional branches (Air Defense Artillery, Adjutant General's Corps, Armor, Aviation, Chemical Corps, Corps of Engineers, Field Artillery, Infantry, Military Intelligence Corps, Military Police, Ordnance Corps, Quartermaster Corps, Signal Corps, and Transportation Corps) and who entered service at pay grades E-4 or below (N = 960,664).

Because we focus on the effects of long-term pollution exposure, we further restrict the sample to individuals who served for at least 5 years by 2019 (N = 315,113). We also require non-missing pollution exposure (initially served in the continental U.S.) and non-missing health care claims between 2015 and 2020 (N = 158,412).[3] Finally, we require an initial assignment to a station with at least 100 personnel in our sample to ensure that we can properly test quasi-random assignment to locations.

Our analytical sample includes 148,681 soldiers who served for at least five years. Summary statistics are provided in **Table 1**. At enlistment, soldiers are 22 years old and will serve an average of 9 years, implying an age of 31 at separation and the end of the observation period. Most soldiers enter at pay grades E-03 (66%) or E-02 (29%). The sample is 55% white, 23% Black, and 15% Hispanic; 87% are male, and 78% are unmarried. Only 3% hold a college degree, while the majority (80%) have only a high school diploma. Mean $PM_{2.5}$ exposure over the course of their service is 7.5 $\mu g/m^3$ well below the U.S. EPA annual standard of 12 $\mu g/m^3$. These values are comparable to levels experienced across the US over the same time period, with an average level of 14.1 in 1990 and 7.81 in 2020.

By construction, the sample is healthy at the time of enlistment. Health, however, deteriorates with age. **Table 2** documents the prevalence of health conditions by the end of the observation period. The first column reports the mean number of diagnoses per soldier, while subsequent columns report rates (per 1,000 soldiers) with at least 1 to 5 diagnoses for each condition. Respiratory conditions afflict 55% of soldiers, while circulatory conditions affect 21%. Within circulatory conditions, hypertension is the most prevalent, affecting 12% of the sample. Respiratory diagnoses are dominated by acute respiratory infection (a short-term condition affecting 41%) but asthma is the most prevalent chronic respiratory condition (6%).

IV- Econometric Strategy

[3] The military conducts regular health examinations and so soldiers are expected to have at least one claim per year corresponding to regular check ups.

a. **Descriptive associations: OLS approach**

We estimate cross-sectional OLS regressions of the following form:

$$y_i = c + \beta \bar{P}_i + e_i \qquad (1)$$

where y_i is a measure of health for individual i; $\bar{P}_i$ is the individual's average $PM_{2.5}$ exposure over the course of their service Standard errors are clustered at the station level to account for common exposure among soldiers in the same station for the persistence of pollution over time.

The coefficient β ideally reflects the causal effect of a 1 $\mu g/m^3$ increase in mean $PM_{2.5}$ exposure on morbidity. However, OLS estimates are likely to be biased for several reasons. First, mean exposure is measured with error (e.g. Richmond-Bryant and Long 2020), which would attenuate the coefficients toward zero. Second, mean exposure may be correlated with unobserved determinants of health. Soldiers have some ability to choose their subsequent assignments and may do so partly in response to air quality (e.g. sicker soldiers may avoid more polluted areas). Such avoidance behavior would bias OLS estimates downward, as has been shown in other contexts (e.g. Moretti and Neidell 2011; Hoffmann and Rud 2024).

Alternatively, location choice may reflect differences in information or socioeconomic advantage. If soldiers with greater resources or better information avoid polluted areas, then OLS may overstate pollution's harm. If, on the other hand, these same soldiers prefer polluted locations (because they are closer to urban amenities, for example), then the impact of pollution will be underestimated. Thus, the net direction of the bias in OLS is ambiguous. Observational studies typically attempt to address these concerns by conditioning on many individual and location covariates, but this approach is insufficient when health and endogenous location choice cannot be convincingly modeled.

We report OLS estimates because they are informative about the magnitude and direction of descriptive associations, which are commonly reported in the literature. Our preferred approach is an instrumental variables strategy. IVs solve measurement error concerns and the issue of endogenous location choice, which results in correlation between the error term and mean $PM_{2.5}$ exposure. Comparing OLS and IV estimates informs us whether descriptive associations over or understate the causal impact of pollution. We discuss the IV approach next.

b. Instrumental variables approach.

We estimate causal effects of long-term exposure to pollution on morbidity by leveraging exogenous variation in average pollution exposure arising from quasi-random assignment to locations within the Army. Military personnel are greatly constrained in their ability to choose residential locations, as moves are determined by the operational needs of the Army. Prior empirical work supports the claim that the timing and frequency of relocations are orthogonal to soldier characteristics (Lyle, 2006; Lleras-Muney 2010; Carter and Skimmyhorn, 2017; Carter and Wozniak, 2023). Thus, their residential location, and resulting $PM_{2.5}$ exposure, is unlikely to correlate with their socioeconomic status or other determinants of health. The idea of using military relocations to investigate the impact of environmental exposures on Army personnel has been successfully used to study short-term effects on children's health (Lleras-Muney 2010).

The intuition is as follows. Upon completing basic training, soldiers with the same occupation, skill level, rank, and enlistment timing are treated equally by the Army because they provide the same type of labor. When demand for this type of labor exists across multiple stations, the Army will allocate this group of soldiers across these stations effectively randomly. This logic supports the exclusion restriction that initial assignment is orthogonal to potential health outcomes. Empirically, on average, the characteristics of soldiers assigned to high and low pollution areas should be the same. We directly test this in the data.

For the instrument to be valid, initial $PM_{2.5}$ exposure must also predict long-term $PM_{2.5}$ exposure. Two features of military service lead to this persistence over time. First, since individuals dislike frequent moving, so the Army limits subsequent migration in order to retain personnel. Since pollution levels are themselves persistent over time within locations, pollution at the initial assignment is predictive of pollution in subsequent years. Second, when relocations do occur, soldiers typically move to stations with similar functional requirements, which tend to have similar pollution levels. This also generates persistence. Therefore, we treat $PM_{2.5}$ exposure in the initial assignment as an instrument for long-term $PM_{2.5}$ exposure, and demonstrate its predictive power below. Specifically, we estimate the following two-stage least squares model:

$$y_i = c + \beta \bar{P}_i + O_i\gamma + e_i \qquad (2)$$

$$\bar{P}_i = PI_i + O_i\delta + \epsilon_i. \qquad (3)$$

Equation (3) is the first stage, where PI_i is $PM_{2.5}$ exposure at the initial assignment location, which we measure one year prior to the assignment. We condition on O_i, the labor group of the soldier. Specifically, O_i is a set of indicator variables for occupation × skill × rank × enlistment quarter group, which constitutes a homogenous type of labor available at a given time from the Army's perspective. Our analytic sample includes 215 occupations, 2 skills, 4 ranks and 68 quarters, resulting in 116,960 potential labor types.

The equation of interest is equation (2), which relates average pollution exposure since enrollment $\bar{P}_i$ to the presence of chronic conditions y_i. We use the predicted pollution in the first stage as an instrument for and control for the weather and for occupation × skill × rank × enlistment quarter dummies O_i. Standard errors are clustered at the base level to account for the fact that all soldiers in the same location experience the same pollution levels and the relative persistence of pollution over time.

The identification assumption is that that conditional on O_i, our instrument, initial pollution PI_i, is orthogonal to e_i. To serve as an instrument we need to demonstrate that conditional on O_i, (i) initial pollution predicts average pollution exposure over all years of military

service (*relevance*), and (ii) that initial pollution affects health only through its effect on average pollution (*exclusion*). We discuss these identifying assumptions and provide evidence in their support next.

c. Testing the validity of the identification approach

We demonstrate that initial pollution exposure is "as good as random" within a type of labor at a point in time. We regress pollution in the initial location on individual characteristics of the soldier. These characteristics are observed at the time soldiers first enlist but, importantly, are not used by the Army to decide on a soldier's location. That is, conditional on the soldier's occupation, skill and rank, their personal characteristics should not influence their location. Specifically, we estimate the following regression:

$$PI_i = X_i\theta + O_i\gamma + \varepsilon_i \qquad (4)$$

where PI_i is the pollution at the soldier's initial location in the year prior to their enlistment, X_i are predetermined characteristics of the soldier at initial assignment (age, race, sex, marital status, education and AFQT score) and O_i is the set of indicator variables defining the soldier's initial labor group. If the Army solely considers the labor group to assign individuals to locations, then the soldier characteristics should not correlate with pollution levels (or any other characteristic of the base) in the initial destination location.

The results of this test are reported in **Table 3.** No soldier characteristic predicts pollution at the initial location prior to their arrival at 5% levels, either individually or jointly (the p-value of the test of joint significance is 0.27). The estimates are also small in magnitude. For example, the coefficient for male soldiers (0.015) is less than 1 percent of the mean $PM_{2.5}$ exposure of 7.5 μg/m³. Other coefficients are similarly modest. These results support our claim that the initial assignment is conditionally as good as random.

While this finding holds for the initial assignment, **Table 3** also shows that this test increasingly fails overtime, consistent with the claim that soldiers gain influence over their

location as they advance in their career within the Army. Estimates for θ for the first year and second year are comparable to estimates for the year prior to their enlistment, which is in line with most assignments lasting for 2-3 years. By year 3, however, the coefficients for certain soldier characteristics increase in magnitude and become statistically significant, with the joint test across all characteristics becoming significant as well. For example, the coefficients for pollution exposure in year 5 indicate that Black soldiers and soldiers with higher AFQT scores live in more polluted locations. The result is not surprising for Blacks: Black civilians are also more likely to be located in polluted areas (e.g. Currie et al. 2023). If soldiers prefer to remain near family or in areas with large Black communities, subsequent relocations may shift them toward higher-pollution bases. The positive association between AFQT scores and pollution is less intuitive, differing from what is observed in the civilian population, but likely reflects that fact that some high-skill occupations in the Army (e.g., mechanical or technical roles) are disproportionately located at more polluted stations.[4]

Although we demonstrated that pollution in the year prior to assignment at the initial assignment location is uncorrelated with soldier characteristics, an even stronger test of our hypothesis is that location is randomly assigned conditional on labor market type. If this is true, then the average characteristics of soldiers in the same labor group should be identical across locations. We test this by estimating the following equation

$$X_{ib} = \lambda_b + O_i\gamma + \epsilon_{ib} \qquad (5)$$

where the dependent variable X_{ib} is an individual characteristic of soldier i sent to base b as their first assignment, $\lambda_b$is a set of indicator variables for each base and O_i is defined as before. We test whether all λ_b coefficients equal each other, that is whether, within a labor group, the average characteristic of soldiers is the same across locations. We follow the RCT literature and use randomization inference to conduct this test as suggested by Kerwin

[4] Individuals drawn from higher socioeconomic strata are more likely to move to locations with lower pollution in the broader population (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011, Finney, Goetzke and Yoon, 2011).

et al. (2025). The results (**Table 4**) show that at the 5% level we cannot reject the null that all the base dummies are 0 for any of the soldier characteristics we explore.

Overall, this evidence supports our assumption that initial pollution exposure is uncorrelated with individual characteristics that may affect health. It also highlights the importance of accounting for endogenous location choice, even among military personnel who face many constraints in choosing their locations. We now present the results of the first stage, which test that the pollution levels in the initial location predict long-term exposure.

d. First-stage results: initial pollution levels predict pollution exposure during military service

To probe the relevance of our instrument over time, we regress $PM_{2.5}$ exposure in year *t* on $PM_{2.5}$ levels in the first assignment location the year *prior* to enlistment, conditional on O_i. **Figure 1** plots the coefficients for each year up to 10 years after enlistment (solid dots). If pollution in the initial location in a given year perfectly predicted subsequent pollution, then the coefficient would equal one. In the first year of assignment, the coefficient is 0.92 suggesting temporal variation in pollution in a given location. Consistent with the fact that very few soldiers are relocated within two years, estimates in the second year are statistically significant and close to those in the first year (0.78). But each year the coefficient declines in magnitude, with a particularly large decline in year 4 when many soldiers relocate (3 years at the time of re-enlistment - military moves are supposed to occur every 12-36 months). There is a steady decline in the coefficient every year thereafter. But even by year 9, the coefficient remains statistically significant (0.06, 95% CI 0.04-0.07).

These patterns are likely driven by the share of individuals that remain at their initial location. Indeed, this fraction (hollow diamonds in **Figure 1**) follows the same pattern as the coefficients: it is above 90% in the second year, and it declines every year, with a large 28 percentage point drop between year 3 and 4. By year 9, however, 16% still remain in their initial location.

How strongly does prior pollution at the initial location predict *average* pollution levels for throughout a soldier's service? The results are given by the last circle in **Figure 1** and show that pollution at the initial location has a statistically significant coefficient of 0.36. This positive and statistically significant coefficient is not driven by the fact that the average pollution includes the initial pollution because our instrument is the level of pollution in the year prior to enlistment so there is no mechanical association in this first stage. The top panel of Figure 2 shows a fairly linear relationship between pollution at the initial location and average pollution in the military in the years thereafter.

This instrument is not weak. The F-statistic for the first stage is 1,201, well above what is required for standard C.I. to be valid (Lee et al. 2025). The magnitude is economically meaningful as well: in the overall sample, the average $PM_{2.5}$ level experienced by a soldier over their career is 7.5. and its standard deviation is 1.8. Increasing $PM_{2.5}$ at the initial location by one standard deviation (3.4) increases average $PM_{2.5}$ levels by (0.36*3.4) 1.2 units, which is 16% of the mean or 36% of a standard deviation.

A potential concern with these results is that pollution levels in the initial assignment might predict the duration of service so that we have two, rather than one endogenous variable (mean pollution and years of service). We test this non-parametrically by regressing initial $PM_{2.5}$ on dummies for the years of service, where the left-out category is 5 years of service, the minimum we require for individuals to enter the sample. Conditional on O_i, none of the coefficients are statistically significant (**Table A.1**). Moreover, a joint test of significance cannot reject the null that all the coefficients are 0 (the p-value of the test of joint significance is 0.16).

e. Exclusion restriction, amenities and weather conditions

Another important concern is that PM2.5 may be correlated with other local characteristics that predict health. In our setting, individuals are randomly assigned to a location (not to a pollution level), and that location may have attributes beyond pollution

that affect health outcomes. This creates two potential sources of confounding: local amenities and weather conditions.

Most soldiers live on or near base, and in this sense the concern about local amenities is less salient than in the general population, as the Army seeks to provide relatively similar living and working conditions across installations. Weather, however, remains an important location-specific factor that we must account for. Pollution is well known to be correlated with meteorological conditions, and many studies document that, at least in the short run, weather directly affects health and mortality (e.g., Carleton et al. 2022). Accordingly, as in most pollution studies, we control for climate as a potential confounder.

We take two approaches to address these issues. First, we present results with and without controls for average weather conditions. Second, we assess robustness to controlling for weather and a broad set of additional local characteristics. Our expectation is that accounting for weather will meaningfully affect the estimates, whereas controlling for other amenities, if indeed they are less relevant in the military context, should have little impact on the estimated effect of pollution. Given the large number of potentially relevant local characteristics, we use LASSO to select the additional controls.

V-The effect of long-term pollution exposure on health

a. Effects on circulatory disease

We begin by investigating impacts on circulatory disease, presenting the OLS and 2SLS estimates of the effect of average $PM_{2.5}$ exposure for reference (**Table 5**). We present two 2SLS estimates, with and without controlling for weather. Our primary outcome is defined as three or more circulatory diagnoses, though we show results for having at least one and up to five or more diagnoses.

For circulatory conditions, both OLS and IV estimates are positive and significant across all diagnostic thresholds. However, the IV estimates are uniformly smaller than their OLS counterparts. For example, when the outcome is defined as having at least three diagnoses, the OLS estimate is 10.9 (s.e. = 1.54), while the corresponding 2SLS with climate controls

estimate is 3.4 (s.e. = 1.5). This pattern suggests that failing to account for endogenous location and selection into polluted areas leads OLS to overstate the impact of pollution, even in a highly constrained setting like the Army. It is also interesting to compare the 2SLS with and without weather. Controlling for weather substantially increases the 2SLS estimates for all specifications, though the estimates in all cases are lower than OLS.

For our preferred definition of chronic morbidity, (at least 3 diagnoses), the "2SLS with climate controls" coefficients imply that a one standard deviation (1.8 $\mu g/m^3$) increase in average pollution exposure to $PM_{2.5}$ results in an increase in the probability of circulatory disease by 5.5 percent (relative to the mean of 112 cases per 1,000). The magnitudes and statistical significance of the estimates are similar across alternative diagnostic thresholds.

Circulatory conditions encompass a wide and heterogenous set of diseases. We explore the effects of pollution exposure on more specific outcomes within this category (**Table 6**). We estimate statistically significant increases in hypertension using our 2SLS estimator but not in other circulatory conditions, though if we include weather controls we also estimate an increase in peripheral vascular diseases. Again here we note that controlling for weather increases the magnitude of the estimates by at least 50%.

The magnitudes we estimate are meaningful: we find that a one s.d. increase in average pollution exposure raises hypertension prevalence by 3.2-4.4 cases per 1,000 soldiers (= 1.8*2.46 or 1.8*1.76 if we do not control for weather), a 4.6%-6.4% increase relative to the mean rate. Hypertension may be a key pathway through which long-term particulate exposure harms circulatory health.

b. Results for respiratory diseases and other conditions.

We next investigate effects on respiratory conditions. Panel b of **Table 5** shows no statistically significant effect using 2SLS regardless of whether we control for climate or how we define the outcome. OLS, by comparison, gives coefficients that are extremely sensitive to this coding, ranging from a *negative* and statistically significant effect of

pollution (when the outcome is having at least one diagnosis) to a positive and statistically significant coefficient that is much larger than the 2SLS coefficient when the outcome is defined as having 5 or more diagnoses.

When we disaggregate respiratory conditions into specific diagnoses (panel b of **Table 6**), we find statistically significant 2SLS effects of average $PM_{2.5}$ exposure on asthma though only if we control for climate. The estimated magnitudes are economically meaningful: a one-standard deviation increase in average exposure is associated with an approximately 7% increase in asthma prevalence. While long-term pollution exposure does not strongly affect broad measures of respiratory morbidity in this population, it impacts specific chronic respiratory conditions such as asthma.

c. Robustness checks

We conduct a series of tests to further assess the validity of our assumptions, using at least 3 encounters as the outcome. First, we assess the role of potential confounding driven by local amenities. Given the large number of potential covariates (71) to include in this model, we estimate a 2SLS model allowing LASSO select the optimal controls. Since weather is an important confounder, though, we force its inclusion in these models.
These results are presented in **Table 7**. We find that regardless of the set of variables we allow LASSO to include, the 2SLS coefficient for circulatory diseases ranges from 2.7 to 4, with none of the estimates significantly different from our model without the local amenities. This pattern of results supports the claim that the Army creates an isolated environment given that other studies typically find that controlling for local amenities significantly impacts the coefficient on pollution. We repeat these exercises for the largest subset of diseases, and we confirm that those results are also robust to the inclusion of other local characteristics.

d. Interpreting IV coefficients

If the effects of pollution exposure are heterogeneous, then 2SLS models do not estimate the average treatment effect for the population but instead estimate the local average treatment effects for the compliers. In our case, the compliers would consist of individuals exposed to more pollution because of the initial pollution assignment. To understand whether this group differs from the average soldier, **Table 10** documents the individual characteristics for compliers and the full sample using Abadie (2002) method. Compliers are largely similar to the population of soldiers in terms of age, share black, share female, marital status and education. They differ primarily in two dimensions: race (more whites and fewer Hispanics) and AFQT (higher AFQT scores). These differences are relatively small, though, suggesting our LATE is unlikely to differ considerably from the ATE.

e. Short- and long-term effects

An advantage of our setting is the ability to identify long-run impacts that may take multiple years to arise and may not arise in the short-run. We assess this by directly estimating the impact of short-term exposure on health. We construct a sample of soldiers whose health outcomes are observed within 180-540 days after each soldier's start date to explore the impact of PM2.5 exposure over a shorter duration. Shown in **Table 8**, we find that these shorter-term windows of exposure do not lead to statistically significant impacts on health and are much smaller in magnitude, suggesting an important difference arises from longer-term exposure.

Our main specification focuses on soldiers with at least 5 years of service, and thus 5 years of exposure. We also probe whether estimates vary with the duration of service, shown in **Table 9**. Although the sample size falls when we restrict to those serving for longer periods, the 2SLS coefficient remains positive and statistically significant for all long durations and appears to increase with duration and then stabilize after 7 years, though the standard errors increase substantially as the sample shrinks making it difficult to precisely estimate the impact of one more year of exposure on outcomes.

VII-Conclusion

This study provides novel evidence on the morbidity effects of long-term particulate matter exposure by exploiting quasi-random assignment of soldiers to locations within the U.S. Army. Using an IV strategy based on initial assignment pollution, we find that sustained PM2.5 exposure has a meaningful effect on circulatory health. In contrast, effects on aggregate respiratory conditions are weaker and imprecisely estimated, though we find significant effects on asthma when focusing on specific chronic diagnoses. These findings are stable across alternative outcome definitions and covariate sets. OLS estimates exceed IV estimates, highlighting the importance of accounting for endogenous location choice.

While prior work has documented acute effects using short-run variation, evidence on sustained exposure remains limited and has relied on observational designs subject to bias due to sorting. By following individuals over time and exploiting quasi-random initial exposure, our approach addresses this concern. The concentration of effects in hypertension is consistent with biological models in which chronic particulate exposure raises cardiovascular risk through cumulative mechanisms rather than repeated acute events. The weaker aggregate respiratory effects may reflect the prevalence of short-term respiratory diagnoses that are less responsive to long-run exposure.

Our findings have important implications for policy and future research. Adverse cardiovascular effects of long-term PM2.5 exposure are documented at concentrations well below the current U.S. EPA annual standard. Existing thresholds may not fully protect against chronic morbidity, even among relatively young and initially healthy populations. While the military setting provides strong internal validity, differences in baseline health, occupations, and demographics may limit external validity. Extending person-based designs to civilian populations remains an important direction for future research.

VII-Tables and Figures

Table 1. Summary statistics

	Mean	SD
Pay grade, initial year		
E01	0.01	0.08
E02	0.29	0.45
E03	0.66	0.47
E04	0.05	0.21
Service length (years)	9.05	4.01
Age, initial year	22.0	3.73
Age, in 2015	27.6	5.57
Race and ethnicity		
White	0.55	0.50
Black	0.23	0.42
Hispanic	0.15	0.36
Asian	0.02	0.15
Sex		
Male	0.87	0.34
Female	0.13	0.34
Marital status, initial year		
Single	0.78	0.41
Married	0.21	0.40
AFQT score		
1	0.04	0.19
2	0.28	0.45
3A	0.26	0.44
3B	0.40	0.49
Educational attainment, initial year		
College degree	0.03	0.16
Associate's degree	0.02	0.14
Some college	0.05	0.22
High school graduate	0.80	0.40
PM2.5 ($\mu g/m^3$) exposure		
Year prior to intitial year	8.9	3.4
Initial year	8.6	3.2
Average over service	7.5	1.8
Soldiers	148,681	

Notes: Summary statistics (means and standard deviations) for the sample of soldiers included in the primary analysis (N = 148,681). The initial year refers to the fiscal year of a soldier's first assignment following Army basic training. Individual characteristics are measured at the time of initial assignment, except for service length (total years of service from initial assignment to discharge) and age in 2015 (measured in 2015, when health outcomes data begin). AFQT denotes Armed Forces Qualification Test scores. PM2.5 is measured at the ZIP-code level, and climate variables are measured at the county level.

Table 2. Prevalence of health conditions

	Diagnoses, per 1000 individuals					
	Count	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Circulatory	1,605	211	142	112	93	79
Hypertension	853	124	86	69	58	50
Peripheral vascular disease	64	20	7.2	4.4	3.2	2.5
Coronary artery disease	79	13	7.5	5.2	3.9	2.9
Heart failure	16	4.0	2.1	1.4	1.0	0.8
Respiratory	3,360	551	379	279	216	173
Chronic obstructive pulmonary disease	65	32	10	5.7	3.4	2.2
Asthma	352	56	36	29	24	20
Acute upper respiratory infection	1,127	417	230	139	90	61
Influenza and pneumonia	173	65	28	17	11	7.6

Notes: Health condition prevalence is derived from diagnosis codes recorded between 2015 and 2020 in Army medical claims, including both on-base and off-base inpatient and outpatient encounters. All values are reported as rates per 1,000 soldiers. Count refers to the total number of diagnosis claims observed, while subsequent columns report prevalence rates, where having a condition is defined as meeting or exceeding the indicated number of diagnoses. ICD-9 and ICD-10 codes used to define each condition are listed in the Appendix.

Table 3. Conditional random assignment of PM2.5

	Prior-year PM2.5	Initial PM2.5	Year 2 PM2.5	Year 3 PM2.5	Year 4 PM2.5	Year 5 PM2.5	Mean PM2.5
Age	0.000	0.001	-0.003	-0.003	-0.007	-0.006	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.001)
Black	0.112	0.095	0.122	0.187	0.337	0.391	0.230
	(0.067)	(0.061)	(0.070)	(0.062)	(0.052)	(0.049)	(0.038)
Hispanic	-0.032	-0.026	-0.020	-0.016	-0.017	-0.029	0.021
	(0.042)	(0.045)	(0.049)	(0.044)	(0.039)	(0.029)	(0.028)
Male	0.015	0.021	0.056	0.035	0.011	-0.002	-0.058
	(0.065)	(0.059)	(0.067)	(0.062)	(0.043)	(0.031)	(0.035)
Single	-0.134	-0.115	-0.121	-0.085	-0.016	0.036	-0.034
	(0.098)	(0.092)	(0.093)	(0.078)	(0.042)	(0.031)	(0.044)
AFQT 1-3A	0.053	0.056	0.042	0.088	0.124	0.127	0.102
	(0.046)	(0.043)	(0.042)	(0.039)	(0.041)	(0.039)	(0.024)
High school graduate only	-0.039	-0.042	-0.017	0.001	0.004	-0.010	-0.009
	(0.032)	(0.031)	(0.033)	(0.033)	(0.027)	(0.028)	(0.014)
F-statistic	1.31	1.50	1.76	4.28	15.9	26.3	10.9
Pr(F ≤ f)	0.27	0.19	0.12	0.00	0.00	0.00	0.00

Notes: Each column reports coefficients from separate regressions of PM2.5 exposure (measured in the year prior to the initial assignment, the initial year, years 2-5, and as the individual's average pollution exposure) on individual characteristics. All specifications include fixed effects for PMOS × SQI × pay grade × quarter, with standard errors clustered at the station level. The F-statistic reports the joint test of statistical significance.

Table 4. Conditional random assignment of initial base

	Age	Black	Hispanic	Male	Single	AFQT 1-3A	HS graduate
BENNING	-0.12	-0.04	0.01	0.02	0.01	0.08	0.06
BLISS	-0.09	-0.03	0.04	0.01	0.00	0.02	0.04
BRAGG	-0.14	-0.04	0.03	0.01	0.01	0.01	0.06
BUCKLEY	-0.33	-0.08	0.08	-0.04	0.06	0.09	0.02
CAMPBELL	-0.09	-0.05	0.01	0.02	0.00	0.02	0.05
CARSON	0.00	-0.07	0.03	0.01	-0.02	0.02	0.04
COINER	-0.63	0.00	0.05	-0.01	0.00	-0.02	0.08
DRUM	-0.11	-0.05	0.03	0.02	0.01	0.03	0.04
EDGEWOOD	-0.08	0.01	0.05	0.02	0.00	-0.01	0.05
EGLIN	-0.35	-0.12	0.01	0.04	0.04	0.20	0.00
EUSTIS	0.13	-0.01	0.02	-0.05	-0.04	0.04	0.06
GEORGE MEADE	-0.07	-0.04	0.00	-0.06	0.02	0.07	0.02
GOODFELLOW	0.18	0.01	0.01	0.01	0.02	0.08	0.07
GORDON	-0.08	0.00	0.01	-0.02	0.00	0.07	0.06
HOOD	-0.15	-0.03	0.05	0.00	0.00	0.00	0.05
HUACHUCA	-0.24	-0.04	0.02	-0.02	0.01	0.07	0.06
HUNTER	-0.14	-0.03	0.01	0.00	0.01	0.07	0.07
IRWIN	-0.08	-0.06	0.05	0.01	0.00	-0.02	0.06
JACKSON	0.24	-0.04	0.05	-0.09	0.02	-0.01	0.06
KATTERBACH	0.55	0.01	-0.07	-0.03	-0.02	0.07	0.03
KNOX	-0.01	-0.07	0.02	-0.01	-0.04	0.02	0.04
LEAVENWORTH	-0.15	-0.06	0.02	-0.07	0.03	0.10	0.07
LEE	0.28	-0.02	0.04	-0.04	-0.01	0.02	0.06
LEONARD WOOD	0.11	-0.05	0.02	-0.01	0.01	0.02	0.05
LEWIS	-0.04	-0.06	0.03	0.01	0.00	0.04	0.06
MYER	-0.36	-0.07	-0.05	0.05	0.04	0.28	0.02
POLK	-0.22	-0.04	0.01	0.02	0.01	0.05	0.04
PRESIDIO	-0.42	-0.08	-0.03	-0.12	0.04	0.26	0.06
REDSTONE	-0.64	0.02	-0.02	0.01	-0.06	0.14	-0.08
RICHARDSON	-0.17	-0.06	0.02	0.01	0.04	0.04	0.07
RILEY	0.01	-0.04	0.02	0.02	-0.02	0.01	0.05
RUCKER	0.48	0.00	-0.01	0.00	-0.02	0.02	0.02
SAM HOUSTON	0.60	0.00	0.05	-0.02	-0.06	0.01	0.09
SCHOFIELD	-0.24	-0.03	0.03	-0.01	0.05	0.01	0.05
SHAFTER	-0.37	-0.03	0.03	-0.06	0.07	0.06	0.08
SILL	0.02	-0.04	0.01	0.03	0.00	0.01	0.03
STEWART	-0.03	0.00	0.02	0.00	-0.01	0.01	0.04
STORY	0.59	0.04	0.04	-0.01	-0.05	0.00	0.01
WAINWRIGHT	-0.39	-0.06	0.01	0.03	0.07	0.03	0.07
WHEELER	-0.13	-0.04	0.05	-0.03	0.06	0.03	0.05
WHITE SANDS	-0.09	-0.01	0.02	0.06	0.04	0.05	0.05
F-statistic	2,261	17,226	140,340	46,627	15,807	204,284	87,204
$Pr(F \leq f)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RI p-value	0.55	0.23	0.07	0.12	0.20	0.07	0.10

Notes: Each column reports coefficients from regressions of individual characteristics on indicator variables for initial station assignment, with ABERDEEN as the reference group. Coefficients represent conditional mean differences in each characteristic across stations after adjusting for PMOS × SQI × pay grade × quarter fixed effects. Standard errors are clustered at the station level. The F-statistic tests the joint significance of all station indicators. The RI p-value reports the randomization inference p-value based on 1,000 simulated draws in which station assignments are randomly re-sampled; it represents the proportion of simulated F-statistics that are more extreme than the observed value.

Table 5. Impact of PM2.5 exposure on circulatory and respiratory conditions

	Diagnoses, rate per 1000 individuals				
	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Circulatory conditions					
Mean	211	142	112	93	79
OLS	10.90	9.66	8.42	7.70	7.00
	(1.33)	(1.00)	(0.98)	(0.94)	(0.91)
2SLS	3.18	2.73	2.12	2.06	1.60
	(1.17)	(0.98)	(0.82)	(0.63)	(0.67)
2SLS with climate controls	4.40	4.19	3.39	3.24	2.75
	(1.66)	(1.30)	(1.15)	(1.04)	(0.94)
Respiratory conditions					
Mean	551	379	279	216	173
OLS	-5.94	-0.48	2.51	3.65	4.14
	(2.46)	(2.07)	(1.91)	(1.68)	(1.49)
2SLS	2.45	1.97	2.58	2.48	2.00
	(1.52)	(2.07)	(1.91)	(1.84)	(1.75)
2SLS with climate controls	2.23	1.17	2.09	2.64	1.72
	(3.61)	(2.74)	(2.31)	(1.99)	(1.58)

Notes: The table reports OLS and 2SLS estimates of the effect of average PM2.5 exposure on circulatory and respiratory conditions, expressed as rates per 1,000 soldiers. Each column corresponds to an alternative definition of the outcome, where having a condition is defined as having at least the indicated number of diagnoses. The OLS estimates regress each health outcome on average PM2.5 without fixed effects. The 2SLS estimates instrument for average PM2.5 using prior-year PM2.5 and include fixed effects for PMOS × SQI × pay grade × quarter. Standard errors are clustered at the station level.

Table 6. Effect of PM2.5 on circulatory and respiratory diagnoses

	Diagnoses, rate per 1000 individuals			
	Mean	OLS	2SLS	2SLS with climate controls
Circulatory conditions	112	8.42 (0.98)	2.12 (0.82)	3.39 (1.15)
Hypertension	69	7.36 (0.86)	1.76 (0.52)	2.46 (0.78)
Peripheral vascular disease	4.4	0.38 (0.11)	0.20 (0.22)	0.42 (0.28)
Coronary artery disease	5.2	0.47 (0.11)	-0.13 (0.17)	-0.18 (0.29)
Heart failure	1.4	0.08 (0.04)	0.01 (0.09)	0.06 (0.14)
Respiratory conditions	279	2.51 (1.91)	2.58 (1.91)	2.09 (2.31)
Chronic obstructive pulmonary disease	5.7	0.56 (0.12)	0.09 (0.21)	0.07 (0.30)
Asthma	29	1.63 (0.34)	0.87 (0.54)	1.23 (0.59)
Acute upper respiratory infection	139	-1.60 (1.25)	0.41 (1.56)	0.48 (2.11)
Influenza and pneumonia	17	0.68 (0.24)	0.47 (0.39)	0.98 (0.46)

Notes: The table reports OLS and 2SLS estimates of the effect of average PM2.5 exposure on circulatory and respiratory conditions, expressed as rates per 1,000 soldiers. Outcomes are defined as having three or more diagnoses for a given condition, with additional rows reporting estimates for selected sub-conditions. The OLS specifications regress each health outcome on average PM2.5 without fixed effects. The 2SLS specifications instrument for average PM2.5 using prior-year PM2.5 and include fixed effects for PMOS × SQI × pay grade × quarter. Standard errors are clustered at the station level.

Table 7. Sensitivity to LASSO-selected county and hospital referral region characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Circulatory conditions, ≥ 3 diagnoses										
2SLS	3.39	3.25	3.52	3.02	3.46	3.46	2.68	2.72	4.00	2.78
	(1.08)	(1.45)	(1.39)	(1.34)	(1.42)	(1.42)	(1.24)	(1.24)	(1.66)	(1.59)
Number of potential controls	-	17	22	33	47	54	67	72	80	84
Number of selected controls	-	5	6	7	6	6	7	7	8	9
Respiratory conditions, ≥ 3 diagnoses										
2SLS	2.09	1.59	1.58	1.76	1.46	1.46	3.62	3.70	2.24	2.70
	(2.18)	(2.86)	(2.75)	(2.76)	(2.80)	(2.80)	(2.41)	(2.42)	(3.56)	(2.81)
Number of potential controls	-	17	22	33	47	54	67	72	80	84
Number of selected controls	-	5	6	7	6	6	7	7	8	9
Potential controls										
Health profession shortage areas		✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor force & employment			✓	✓	✓	✓	✓	✓	✓	✓
County typology and rurality				✓	✓	✓	✓	✓	✓	✓
Federal expenditures					✓	✓	✓	✓	✓	✓
Local expenditures						✓	✓	✓	✓	✓
Crime							✓	✓	✓	✓
Medicare mortality								✓	✓	✓
Medicare reimbursements									✓	✓
Medicare HEDIS screenings										✓

Notes: The table reports 2SLS estimates of the effect of average PM2.5 exposure on circulatory and respiratory conditions, defined as having three or more diagnoses, expressed as rates per 1,000 soldiers. Estimates are obtained using the partialling-out LASSO instrumental variables procedure described in Chernozhukov, Hansen, and Spindler (2015). Column (1) reports the baseline specification. Subsequent columns sequentially expand the set of potential controls from which LASSO selects, illustrating the sensitivity of the 2SLS estimates to the inclusion of additional covariates. In column (9), LASSO selects 5 geographic controls from a pool of 71 candidate geographic variables. All specifications control for average climate variables, and standard errors are clustered at the station level.

Table 8. Effect of short-run PM2.5 on circulatory and respiratory conditions

	Diagnoses				
	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Circulatory conditions, ≥ 3 diagnoses					
Mean	73	42	29	23	18
2SLS	1.52	-0.71	-0.78	-0.45	-0.33
	(0.99)	(0.99)	(1.03)	(0.95)	(0.77)
Respiratory conditions, ≥ 3 diagnoses					
Mean	521	312	196	130	90
2SLS	2.29	3.12	3.10	0.82	0.35
	(2.91)	(2.02)	(1.63)	(1.92)	(1.55)
Soldiers			47,311		

Notes: The table replicates the primary analysis but removes the restriction on years of service and measures health outcomes within the short-run window of 180 to 540 days after each soldier's start date. As in the main specification, outcomes are expressed as rates per 1,000 soldiers and defined based on the number of diagnoses for circulatory and respiratory conditions. OLS estimates regress each outcome on average PM2.5 without fixed effects, while 2SLS estimates instrument for average PM2.5 using prior-year PM2.5 and include fixed effects for PMOS × SQI × pay grade × quarter. Standard errors are clustered at the station level.

Table 9. Effect of long-run PM2.5 on circulatory and respiratory conditions

	Service length (years)					
	≥ 5	≥ 6	≥ 7	≥ 8	≥ 9	≥ 10
Circulatory conditions, ≥ 3 diagnoses						
Mean	112	123	136	149	161	172
2SLS	2.12	2.70	3.11	3.28	3.23	2.92
	(0.82)	(1.06)	(1.21)	(1.32)	(1.80)	(2.51)
Respiratory conditions, ≥ 3 diagnoses						
Mean	279	291	304	319	333	344
2SLS	2.58	2.53	2.33	2.58	1.05	0.74
	(1.91)	(1.71)	(1.52)	(1.95)	(2.39)	(2.92)
Soldiers	148,681	120,458	95,795	77,568	63,246	51,494

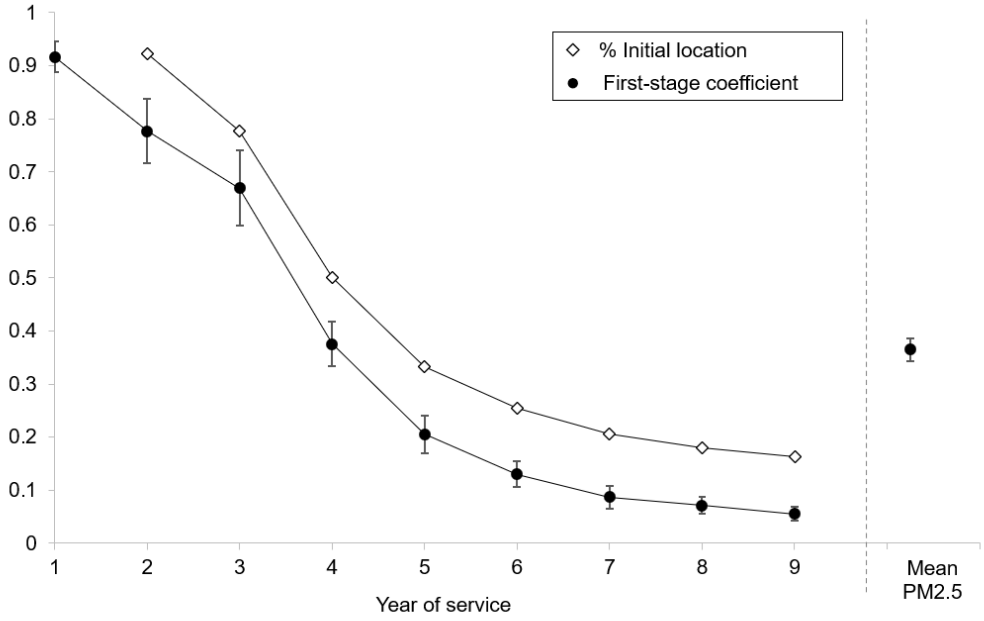
Notes: The table reports the primary 2SLS estimates of the effect of average PM2.5 exposure on circulatory and respiratory conditions, defined as having three or more diagnoses and expressed as rates per 1,000 soldiers. Columns sequentially restrict the sample to soldiers with a minimum length of service, beginning with at least 5 years and increasing through at least 10 years of service. All models instrument for average PM2.5 using prior-year PM2.5, include fixed effects for PMOS × SQI × pay grade × quarter, and cluster standard errors at the station level.

Table 10. Complier characteristics

	Full sample	Compliers
Service length (years)	9.05	8.87
Age, initial	22.0	22.1
Age, in 2015	27.6	27.9
Race and ethnicity		
White	0.55	0.57
Black	0.23	0.26
Hispanic	0.15	0.13
Sex		
Male	0.87	0.87
Female	0.13	0.13
Marital status, initial		
Single	0.78	0.77
Married	0.21	0.22
AFQT 1 - 3A	0.57	0.61
High school graduate	0.80	0.79

Notes: The table compares individual characteristics for the full sample and the subgroup of compliers, estimated using the Abadie's (2003) κ method. Compliers are individuals whose average exposure to PM2.5 is affected by the prior-year PM2.5.

Figure 1. First-stage coefficients and station persistence rates



Coefficient	0.92	0.78	0.67	0.38	0.21	0.13	0.09	0.07	0.06	0.36
F-statistic	4,244	670	370	331	143	114	67	77	68	1,201

Notes: The figure plots station persistence and first-stage relationships between PM2.5 exposure across years of service. Diamonds represent the proportion of soldiers whose assigned station remains the same as their initial assignment, by year of service. Circles represent the first-stage coefficients from regressions of PM2.5 exposure in years 1-9 on prior-year PM2.5, capturing the persistence of exposure across assignments. The final point ("Mean PM2.5") shows the coefficient from a regression of average PM2.5 across all service years on prior-year PM2.5. Coefficients and corresponding F-statistics from these regressions are reported below the figure. All specifications include fixed effects for PMOS × SQI × pay grade × quarter, and standard errors are clustered at the station level.

Table A1. Association between prior-year PM2.5

	Prior-year PM2.5
Service length (ref: 5 years)	
6 years	0.03 (0.04)
7 years	-0.01 (0.03)
8 years	0.02 (0.04)
9 years	-0.01 (0.05)
10 years	0.07 (0.04)
≥ 11 years	0.06 (0.04)
F-statistic	1.63
Pr(F ≤ f)	0.16

Notes: Estimates represent coefficients from a regression of prior-year PM2.5 exposure on indicator variables for service length, with 5 years of service as the reference category. All models include fixed effects for PMOS × SQI × pay grade × quarter, and standard errors are clustered at the station level.

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