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ABSTRACT

We provide the first causal evidence on how long-term exposure to fine particulate matter (PM_{2.5}) at contemporary ambient levels contributes to the development of chronic disease in a young, 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 that we use as an instrument for average annual pollution exposure over a soldier's career. We find that sustained PM_{2.5} exposure substantially increases circulatory disease, particularly hypertension, with mixed evidence on respiratory conditions that are sensitive to specification. Exposure over shorter durations, by contrast, has little detectable effect, a pattern consistent with the cumulative nature of pollution's health burden. These findings demonstrate that even moderate long-term exposure to air pollution 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 experience pollution as a steady, low-to-moderate exposure over many years. A growing literature documents that even short-run fluctuations in air pollution harm 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-term exposure to fine particulate matter (PM_{2.5}) impacts the onset of chronic disease in a young, initially healthy population.

It is notoriously challenging to find a setting in which to properly estimate the impacts of long-term exposure. Much of our evidence on the effects of long-term 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 preferences for local amenities (Banzhaf and Walsh, 2008; Gamper-Rabindran and Timmins, 2011; Finney, Goetzke and Yoon, 2011; De Silva et al., 2024). 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-term effects. This endogenous sorting of people to places generates confounding variation that obscures pollution's independent, long-term effect.

We address this challenge by focusing on U.S. Army soldiers and exploiting a unique feature of its 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-term 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% of Americans of prime recruiting age meet military 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 health care 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.

We assemble a unique dataset that allows us to track long-term 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-term PM_{2.5} exposure leads to pronounced increases in circulatory morbidity, with a 1 standard deviation increase in PM_{2.5} resulting in a statistically significant 5.5% increase. Disaggregated results suggest that this circulatory effect is driven primarily by hypertension. The estimates for respiratory conditions reveal a smaller 1.3% statistically insignificant increase. At the diagnosis level, however, the evidence points to increases in asthma and influenza/pneumonia, though the statistical significance of these estimates varies depending on the specification. Exposure over shorter durations, by contrast, has little detectable effect in this young and healthy population, a pattern consistent with the cumulative nature of pollution's health burden. Notably, naïve OLS estimates in our sample yield inconsistent and frequently counterintuitive associations between pollution and disease, demonstrating that observational correlations can be misleading when sorting is not addressed.

Our analysis contributes to a nascent literature that seeks to estimate the elusive causal effects of long-term air pollution exposure. Foundational studies in China have 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 U.S., 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; Barreca 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 may be difficult to validate when exposure is defined for places rather than people. Recent

work by Deryugina and Reif (2025) makes headway on this limitation by embedding quasi-experimental estimates of short-run pollution shocks on mortality into a structural model to project long-term survival effects among the elderly population.

We complement this work in three important ways. First, whereas most quasi-experimental studies identify long-term 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-term exposure that is tied to individuals rather than places.¹ Nonetheless, like all studies of long-term 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 for all soldiers, regardless of their location. Thus, while pollution levels will differ across military bases, most other amenities will not. Third, soldiers' frequent reassignments reduce their opportunities to integrate into local communities. Consistent with these points, our estimates remain quite stable when we use LASSO regression to select among 70 location-specific characteristics as potential confounders.

Our second contribution is a focus on morbidity rather than mortality, allowing us to capture earlier stages of disease progression that have significant implications for long-term welfare. While mortality is a costly outcome when it occurs, it is relatively rare and only captures the most severe health effects of pollution. Moreover, these effects are concentrated among frail populations — typically very young children or the elderly. In

¹ As previously noted, Deryugina and Reif (2025) address endogenous residential location choices by relying on a structural model to extrapolate long-term effects from short-run pollution shocks. Our approach differs by exploiting conditionally random assignment to locations.

contrast, morbidity is more prevalent, especially in a younger and generally healthy population, and thus provides a more sensitive measure of pollution's potentially cumulative physiological burden. In addition, morbidity is important in its own right, since it can reduce welfare for many years before any effects are reflected in mortality.

Finally, 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, 2025). The mean PM_{2.5} value of 7.5 µg/m³ in our sample is almost identical to the current national average of 7.3 µg/m³ (EPA, 2025) and well below current air quality standards of 9 µg/m³.

Overall, 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-term 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 re-evaluating current air-quality standards and their ability to protect long-term health and human capital. Our findings suggest that long-term exposure at the ambient concentrations that prevail in the contemporary U.S. is detrimental to health.

II-Institutional Setting

This section provides the background for our empirical approach in two parts. We begin by briefly summarizing the health rationale for focusing on long-term PM_{2.5} exposure, and then describe the institutional features of Army service that generate useful variation in cumulative exposure across soldiers.

a. The effects of PM_{2.5} on health

A large medical and epidemiological literature links long-term air pollution exposure to adverse health, particularly through respiratory and circulatory pathways. Fine particulate matter (PM_{2.5}) can penetrate deep into the lungs and enter the bloodstream, where it is believed to contribute to systemic inflammation, oxidative stress, and vascular dysfunction (Møller et al. 2014; Glencross et al. 2020; Alfano et al. 2018). Over time, repeated exposure may accelerate the development of chronic conditions affecting the respiratory and circulatory systems, including asthma, chronic obstructive pulmonary disease, coronary heart disease, stroke, and heart failure, among others (Pope and Dockery 2006). As a result, even modest increases in exposure, when experienced persistently, may substantially elevate long-term morbidity and mortality risk.

Short-term and long-term exposure likely affect health through related but distinct mechanisms. Acute exposure can generate transient physiological responses, including airway irritation, vasoconstriction, and temporary systemic inflammation (Brook et al. 2010). Chronic exposure, by contrast, is the accumulation of these insults over time, which may lead to structural and functional changes in organs, including airway remodeling, plaque formation in arteries, and persistent immune dysregulation (Pope and Dockery 2006; Brook et al. 2010). Thus, while short-term spikes may trigger acute episodes, long-term exposure is more likely to shape disease incidence and progression by gradually altering baseline physiological function.

b. Personnel selection and relocation in the US Army

The U.S. Army provides a useful setting for studying the health effects of long-term pollution exposure because recruits are extensively screened before entering service. Most chronic medical conditions are disqualifying for enlistment, including conditions we study in this paper, such as asthma and hypertension (DoWI 6130.03-V1, 2018). The enlisted population is therefore unusually healthy at baseline, which implies that chronic conditions observed during service are more likely to reflect new rather than preexisting diseases.

Applicants who pass this initial health screening take the Armed Forces Qualification Test (AFQT), a standardized exam covering math, verbal, and related reasoning skills that is

widely used as a measure of general aptitude (DoDI 1145.01, 2013). AFQT scores matter along two margins. First, they help determine whether an applicant is eligible to enlist. Second, conditional on entry, they determine the set of military occupations and training programs for which a recruit qualifies. Thus, AFQT helps shape both selection into the Army and sorting across specialties within it.

After enlistment, all recruits complete ten weeks of basic combat training. Advanced individual training follows and is specific to the recruit's military occupational specialty, with duration and content varying across specialties. Entry into these specialties is not unconstrained. Recruits may choose only among occupations for which they qualify based on AFQT performance and for which training slots are available at the time of enlistment. Thus, while soldiers have some influence over the type of work for which they train, that influence is limited and exercised primarily at the level of occupation rather than location.

This distinction matters because the Army assigns soldiers to installations based on its demand for types of labor. Each quarter, the Army Human Resources Command compiles information from bases on their staffing needs by occupation and skill. These needs reflect operational requirements, the mix of units stationed at a base, planned rotations, and broader Army priorities. As a result, the set of feasible locations for a newly trained soldier depends both on the specialty for which that soldier trained and on the Army's contemporaneous demand for that type of labor. A helicopter mechanic, for example, can be assigned only to installations that host the relevant aviation units, and even within that subset, available postings vary over time with the Army's needs.

The supply side of this process is constrained as well. In any given quarter, the Army's pool of available personnel depends on who enlisted earlier, which specialties they qualified for, which contracts were open when they enlisted, and how many soldiers completed training in each field. From the recruit's perspective, neither the set of future openings nor their geographic distribution is knowable at the time of enlistment. As a result, soldiers do not choose their initial duty station and cannot easily anticipate which locations will have vacancies in their field at the time that they enlist.

Initial duty-station assignments are determined primarily by the Army's operational needs. The Army Human Resources Command allocates newly trained soldiers across installations to fill staffing requirements within occupation-skill groups. In practice, this means that the first posting depends on the intersection of a soldier's qualifications and the Army's contemporaneous personnel demands rather than on the soldier's preferred destination. Conditional on the type of labor a soldier supplies, initial assignment therefore reflects the Army's manpower needs across installations.

This feature of the personnel system is important for our analysis because it generates meaningful variation in early-career geographic exposure across otherwise similar soldiers. Soldiers in the same occupation and skill may be sent to different installations as the Army responds to changing staffing needs across bases. As a result, the location at which a soldier begins service is determined by centralized personnel allocation rather than by individual residential choice.

Subsequent assignments are different. Later postings allow greater scope for soldier preferences, particularly around reenlistment, when the Army has stronger incentives to accommodate soldiers' preferences for retention purposes. Thus, while initial assignment to a base, and the associated pollution exposure, is plausibly random conditional on occupation and skill, subsequent assignments are more likely to reflect both Army demand and soldier preferences. This distinction motivates the empirical strategy described in Section IV.

III-Data

We combine administrative data on Army personnel and health care utilization with pollution, climate, and area-level contextual data to construct the sample. These sources differ in their temporal coverage: our personnel and exposure data begin in 1999, but the health care utilization data begin only in 2015. As a result, although we can assign exposure to soldiers prior to 2015, we observe health outcomes — and therefore include

soldiers in the estimation sample — only for soldiers with at least one medical record between 2015 and 2020.

Since our object of interest is long-term pollution exposure, we conduct the analysis at the annual level. Assignment location is observed in the personnel records at the zip code level, making zip code the relevant geographic unit.² We begin by describing the component data sources.

a. Data sources

Army personnel data: 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 from 1999 to 2019. The data include 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 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 the set of locations where that soldier may serve. For example, a soldier with a PMOS 11B (Infantryman) occupation may be assigned to any of the large number of installations with infantry units, such as Fort Campbell or Fort Hood. However, if that soldier also holds the SQI "P" (Parachutist) skill, the set of feasible assignments narrows to installations with airborne billets, such as Fort Bragg.

Health care claims data: We combine health care claims data from 2015 to 2020 across multiple sources. These include 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 the TRICARE Encounter

² The majority of soldiers live on the base they are assigned to or nearby (Pint et al., 2024). 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.

Data Institutional (TEDI) for TRICARE inpatient care. These data capture interactions that soldiers and their dependents have with the health care system and include diagnosis information based on ICD-9 and ICD-10-CM codes.

Pollution data: Measuring pollution exposure across Army bases requires data with consistent national coverage, including in rural areas where monitoring networks are sparse. We therefore use annual data on fine particulate matter concentrations (PM_{2.5}) derived from the 1 km-by-1 km product of Van Donkelaar et al. (2021), which combines ground-based measurements, satellite retrievals, and chemical transport models to estimate ambient PM_{2.5} concentrations across the entirety of the U.S. We map these grid-level pollution data to zip codes using the pollution value at the grid cell corresponding to the population-weighted centroid of each zip code. We then link these annual zip code measures to soldiers using the zip code of the unit to which they are assigned.³

Climate data: Climate has a well-established impact on both health (e.g. Deschenes and Greenstone, 2011; Carleton et al., 2022) and pollution formation (Sillman and Samson, 1995; Coates et al., 2016), 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 the military personnel records. Meteorological data come from NASA’s Daymet project, which provides daily information on temperature and precipitation. We compute annual precipitation in millimeters. To account for nonlinear temperature effects, we compute average annual temperature, the annual number of days with temperature below 32°F, and the annual number of days with temperature above 90°F. We measure climate exposure as the annual average across all base assignments observed in the sample.

Other data: We also draw on several external sources to characterize the broader areas in which soldiers are assigned. Economic characteristics come from County Data Books

³ Since the geographic measures of location (and thus pollution assignment) and local amenities differ for soldiers stationed abroad, we only assign pollution (and climate) to soldiers while stationed in the US. We omit soldiers stationed overseas for their first assignment. For soldiers stationed overseas in later assignments, we exclude that year when assigning pollution.

(ICPSR #20660) and are measured at the county level. These variables include demographic information (e.g., population size), economic indicators (e.g., labor force participation, unemployment, poverty, and education), health professional shortage areas, public expenditures in various domains, and crime. Information on health care availability and quality comes from the Dartmouth Atlas and is measured at the hospital referral region level. These variables include mortality rates among the Medicare population, Medicare reimbursement rates, and a variety of measures of health care performance. All area-level variables are assigned based on the county or hospital referral region in which the soldier's unit zip code is located. All such measures are constructed using average values over the 2000-2007 period, a window that predates both the Great Recession and our health outcome observation period, ensuring that local conditions are measured before they could be influenced by the outcomes under study. Altogether, we use more than 70 variables to capture broader economic, social, and health care characteristics that could confound the relationship between pollution exposure and health outcomes.

b. Outcomes of interest

As noted earlier, particulate pollution is believed to be linked to both circulatory and respiratory health. We therefore examine diagnoses in these two categories using the claims data, constructing separate indicators for whether an individual is diagnosed with a circulatory or respiratory condition based on ICD-9 and ICD-10-CM codes.

Circulatory diagnoses correspond to codes 390-459 in ICD-9 and I* in ICD-10-CM, while respiratory diagnoses correspond to codes 460-519 in ICD-9 and J* in ICD-10-CM. Because each category contains conditions that differ in severity, economic consequences, and the likelihood that they appear within our observation window, we also unpack them by examining the four most frequent population-level diagnoses within each. Within circulatory conditions, these are hypertension, peripheral vascular disease, coronary artery disease, and heart failure. Within respiratory conditions, they are asthma, chronic

obstructive pulmonary disease, acute upper respiratory infection, and influenza and pneumonia.

This disaggregation is useful because these conditions differ substantially in how likely they are to arise in a young adult population: for example, roughly 7.5% of the U.S. population aged 18-39 has hypertension (Fryar et al. 2017), whereas heart failure is far less common at these ages. Similarly, about 8% of people aged 22-39 have asthma, while fewer than 2% have COPD (CDC 2021). Examining these diagnoses separately helps clarify which conditions drive any overall relationship between pollution exposure and health.

A key challenge in using claims data to define outcomes is distinguishing potentially transient events from more sustained health conditions. A single claim may reflect an isolated episode, a provisional diagnosis, or a coding irregularity rather than a meaningful underlying condition. To reduce measurement error from such one-off events, we classify a soldier as having a condition only if the soldier has at least three claims carrying diagnoses for that outcome, following Gershon et al. (2009). We also report results using alternative thresholds ranging from one to five claims. Our preferred measures therefore place less weight on isolated diagnoses and more weight on conditions that generate repeated contact with the health care system during the 2015-2020 observation period.

c. Sample construction and descriptive statistics

We next describe the construction of the estimation sample and summarize its main characteristics. 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 our analysis focuses on long-term pollution exposure, we restrict the sample to soldiers who had completed at least five years of service by 2019, ensuring sufficient exposure duration within the sample period ($N = 315,113$). This restriction, however, excludes soldiers who left before the five-year mark, making endogenous reenlistment a potential concern — soldiers exposed to higher cumulative pollution in their first few years of service may not reenlist and would therefore not be included in our sample. If soldiers who leave or are separated via medical discharge because their health deteriorates prior to the five-year mark are likely to be those most affected by cumulative pollution exposure, then their exclusion could affect our estimates, although the direction of the resulting bias is unclear a priori.

We then retain soldiers with non-missing pollution exposure, which limits the sample to those whose initial service was in the continental U.S. ($N = 257,313$). Next, we require non-missing health care claims between 2015 and 2020 ($N = 158,412$).⁴ Finally, we impose two restrictions to ensure sufficient cell sizes for our analyses: 1) that the initial station assignment has at least 100 personnel in our sample; and 2) that the conditions for random assignment in each quarter (as defined in the next section) yield more than one soldier. These restrictions yield a final analytic sample of 148,681 soldiers.

Summary statistics for this sample are reported in **Table 1**. At enlistment, soldiers are 22 years old and will serve an average of 9 years, implying an average age of 31 at separation. Because we do not have administrative data on soldiers after leaving their service, service exit ends our observation of a given soldier. 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

⁴ To be clear, soldiers receive annual checkups while actively serving and thus generate at least one claim per year. The large reduction in sample size at this step is driven by soldiers who separated before the health claims observation window opened in 2015.

only a high school diploma. Mean PM_{2.5} exposure over the course of their service is 7.5 $\mu\text{g}/\text{m}^3$, well below the current U.S. EPA annual standard of 9 $\mu\text{g}/\text{m}^3$.

By construction, the sample is healthy at the time of enlistment. Health, however, deteriorates with age. **Table 2** documents the prevalence of health conditions in the observation period. The first column reports the total count of diagnoses per 1,000 soldiers, while subsequent columns break down this figure into counts of soldiers with at least 1 to 5 diagnoses for each condition. Focusing on at least 3 diagnoses (our primary dependent variable), 11.2% of soldiers are diagnosed with circulatory conditions and 27.9% are diagnosed with respiratory conditions. Within circulatory conditions, hypertension is the most prevalent, affecting 6.9% of soldiers and accounting for 62% of all circulatory conditions. Respiratory diagnoses are dominated by acute respiratory infections, which affect 13.9% of soldiers and account for 49.8% of all respiratory conditions. The corresponding values for asthma, the next most common respiratory condition, are 2.9 and 10.3%.

IV- Econometric Strategy

Our object of interest is the effect of long-term PM_{2.5} exposure over a soldier's Army career on subsequent morbidity. An OLS regression of health outcomes on observed pollution is unlikely to have a causal interpretation because of the endogenous assignment of pollution: individuals who live in higher pollution areas differ systematically from those in lower pollution areas. The direction of this bias is theoretically ambiguous and depends on the margin of sorting.⁵ Wealthier individuals tend to pay for cleaner air, but they also concentrate in denser, more economically productive areas that carry higher pollution burdens. Measurement error in pollution exposure introduces a further complication, as classical attenuation bias would obscure any true relationship regardless of its direction. We therefore focus on IV estimates for causal interpretation and report OLS only as a descriptive benchmark.

⁵ See Banzhaf and Walsh (2008), Gamper-Rabindran and Timmins (2011), and Finney, Goetzke and Yoon (2011) on amenity sorting, and Glaeser et al. (2001) and Albouy (2016) on sorting toward dense, high-amenity areas.

To identify this causal effect, we employ an instrumental variables strategy that exploits variation in exposure induced by initial assignment within the Army. The key identifying assumption we make is that conditional on occupation, skill, rank, and quarter of assignment, soldiers assigned to different installations are observationally equivalent but face different local pollution environments. We use this variation as a plausibly exogenous source of differences in long-run pollution exposure.

This strategy relies on two assumptions. First, pollution at the initial assignment must predict average pollution exposure over the course of service (relevance). Second, holding fixed a soldier's occupation, skill, rank, and quarter of assignment, pollution at the initial assignment is orthogonal to potential health outcomes (exclusion). We discuss each condition in turn before formalizing the resulting two-stage least squares specification.

The relevance condition follows from the persistence of exposure over military careers. This persistence reflects the fact that soldiers often remain at their initial assignment for some time, particularly early in their careers. In addition, subsequent relocations remain constrained by Army assignment patterns, which further reinforces persistence in exposure. For these reasons, pollution at the initial assignment is a strong predictor of average pollution exposure over the course of service, a relationship we confirm in the first-stage regression.

The exclusion restriction follows from the Army assignment process described above. Soldiers with the same occupation, skill, and rank who are assigned in the same quarter supply the same type of labor to the Army at the same point in time. Their initial assignments are determined by the Army's staffing needs across feasible locations rather than by individual preferences. When more than one installation is feasible, this process generates variation in initial location across otherwise similar soldiers. Accordingly, within these occupation-skill-rank-by-quarter cells, initial assignment is plausibly orthogonal to potential health outcomes. Prior work using military relocations finds that the timing and frequency of assignment are orthogonal to individual characteristics in ways that are useful

for identification of place effects (Lyle 2006; Lleras-Muney 2010; Carter and Skimmyhorn 2017; Carter and Wozniak 2023). We assess this implication directly by testing whether predetermined soldier characteristics predict pollution at the initial posting.

We formalize this strategy using the following two-stage least squares system:

$$\bar{P}_i = \pi PI_i + O_i \delta + \epsilon_i. \quad (1)$$

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

Equation (1) is the first stage, where PI_i , the PM_{2.5} level at soldier i 's initial assignment location — measured in the year prior to assignment — is used to instrument for $\bar{P}_i$, the soldier's average PM_{2.5} exposure over the course of their military service. As discussed above, we condition on a full set of occupation $\times$ skill $\times$ rank $\times$ quarter-of-assignment indicators (O_i), which define the soldier's labor group and therefore the set of locations to which that soldier can plausibly be assigned.

Equation (2) is the second stage and relates morbidity (y_i) to average pollution exposure over the course of service. In our baseline specification, we include the same occupation $\times$ skill $\times$ rank $\times$ quarter-of-assignment fixed effects used in the first stage. Standard errors are clustered at the base level to account for common pollution exposure among soldiers assigned to the same location and for the persistence of pollution within locations over time.

In addition to focusing on mean pollution exposure, we also estimate models that include the number of service years in which the annual average of PM_{2.5} exceeds 9 $\mu\text{g}/\text{m}^3$, the current National Ambient Air Quality Standards (NAAQS). This measure captures the persistence of exposure above a policy-relevant threshold rather than average pollution alone. If the relationship between PM_{2.5} and health is nonlinear, this measure may better characterize long-term environmental risk than the mean annual concentration.

One implication of our specification is that we do not explicitly model differences in service length across soldiers. Our treatment is defined as average PM_{2.5} exposure over the period of military service observed in the data, rather than cumulative exposure. Therefore, a potential concern is that service length may itself respond to pollution exposure, which could induce selection through differential attrition.⁶

We assess this implication in two ways. First, we directly examine whether pollution at initial assignment predicts subsequent service duration. As we demonstrate below, we do not find evidence of such an effect. This suggests that differential attrition is unlikely to be a primary driver of our results.

Second, as an alternative to average exposure, we construct cumulative PM_{2.5} exposure while controlling flexibly for years served. Because initial PM_{2.5} does not predict years served, conditioning on service length is unlikely to introduce substantial post-treatment bias. When focusing on mean pollution, we include the sum of annual PM_{2.5} exposure over observed service years. For the threshold approach, we sum the number of years in which PM_{2.5} exceeds 9 µg/m³.

c. Testing the validity of the identification approach

We begin by testing whether pollution at the initial posting is systematically related to predetermined soldier characteristics. Specifically, we regress pollution at the initial location on characteristics observed at enlistment but not used by the Army in making location assignments, including age, race, sex, marital status, education, and AFQT score. Conditional on the soldier's labor group, these characteristics should have little predictive power for pollution at the initial assignment if assignment is as good as random within labor groups. Formally, we estimate

$$PI_i = X_i\theta + O_i\gamma + \varepsilon_i \quad (3)$$

⁶ Although we include quarter-of-assignment fixed effects to account for cohort-specific factors, these controls do not fully eliminate individual variation in service length.

where PI_i is the pollution at the soldier's initial location in the year prior to their assignment, X_i is a vector of predetermined soldier characteristics at initial assignment 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 other 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 conventional significance levels (5%), 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% of the mean PM_{2.5} exposure (7.5 $\mu\text{g}/\text{m}^3$) or its standard deviation (1.8). Other coefficients are similarly modest. These results support our claim that the initial assignment is conditionally as good as random.

Table 3 also shows that this test increasingly fails over time, 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 and second year are comparable to estimates for the year prior to their assignment, which is in line with most assignments lasting two to three years. By year 3, however, the coefficients for certain soldier characteristics increase in magnitude and become statistically significant, and the joint test across all characteristics becomes significant as well. By year 5, for example, the estimates indicate that Black soldiers and soldiers with higher AFQT scores (scores categorized by the Army in groups 1, 2 and 3A) locate in more polluted areas. The result for Black soldiers is not surprising: Black civilians are also more likely to live in polluted areas (e.g., Currie et al. 2023). If soldiers prefer to remain near family or in areas with larger 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 it may reflect the fact that some high-skill occupations in the Army (e.g., mechanical or technical roles) are disproportionately located at more polluted stations.

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

$$X_{ib} = \lambda_b + O_i\gamma + \epsilon_{ib} \quad (4)$$

where the dependent variable X_{ib} is an individual characteristic of soldier i stationed at base b for their first assignment, λ_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 the average characteristics of soldiers are the same across locations within a labor group. We follow the randomized-control-trial literature and implement this test using randomization inference, as suggested by Kerwin et al. (2025). **Table 4** shows that, at the 5% level, we cannot reject this null for any of the soldier characteristics we examine.

Next, we turn to the first stage: pollution at the initial assignment must predict subsequent pollution exposure over the course of service. To examine this directly, we estimate a “dynamic” first stage by regressing PM_{2.5} exposure in year t on PM_{2.5} at the initial assignment location in the year prior to assignment, conditional on the labor-group fixed effects (O_i). **Figure 1** plots the resulting coefficients for each year, up to ten years after enlistment. If pollution at the initial location perfectly predicted subsequent pollution, the coefficient would equal one. In practice, the first-year coefficient is 0.92, reflecting some temporal variation in pollution within locations. The second-year estimate remains large at 0.78, consistent with the fact that very few soldiers are relocated within two years. The coefficient then declines over time, with a particularly large drop between years 3 and 4, when many soldiers face a re-enlistment decision that often leads to relocation. Nonetheless, the coefficient on initial pollution remains statistically significant even by year 9 (0.06, 95% CI 0.04-0.07).

These patterns closely track the fraction of soldiers who remain at their initial location. As shown by the hollow diamonds in **Figure 1**, this share remains above 90% in year 2, drops sharply between years 3 and 4, and is still 16% by year 9. Pollution at the initial posting therefore predicts later pollution exposure both because soldiers often remain in place for several years and because subsequent relocations do not fully break the link between initial and later environments.

Since we do not use the dynamic first stage results in equation (1), the final point in **Figure 1** summarizes the key first-stage relationship for the 2SLS design: how strongly prior pollution at the initial location predicts average pollution exposure over the course of service. The estimated coefficient is 0.36 and is highly statistically significant.

This instrument is strong by conventional standards. The first-stage F-statistic is 1,201, well above thresholds for reliable inference (Lee et al., 2025). The magnitude is economically meaningful as well. In the analytic sample, average $\text{PM}_{2.5}$ exposure over a soldier's career is $7.5 \mu\text{g}/\text{m}^3$, with a standard deviation of 1.8. Using our first stage estimate of 0.36 implies that a one-standard-deviation (3.4) increase in $\text{PM}_{2.5}$ at the initial assignment location raises average pollution exposure over the course of service by about $1.2 \mu\text{g}/\text{m}^3$, or roughly 16% of the mean and 68% of a standard deviation of average career exposure.

Next, we show a binned scatter plot of the relationship between initial pollution and long-term pollution using the methods from Cattaneo et al. (2024). Although monotonicity is not required for two-stage least squares estimators to be consistent, monotonicity ensures that the instrumental variable estimates are interpretable if treatment effects are heterogeneous. **Figure 2** shows that the relationship is tight, linear, and monotonically increasing across the full range of initial assignment pollution values.

One remaining concern is that pollution at the initial assignment might also predict duration of service. Soldiers assigned to more polluted bases may differentially exit the military because of their pollution exposure or resulting health impacts. In this case, the

instrument would shift both average pollution exposure and years spent in the Army. We test this non-parametrically by regressing initial PM_{2.5} on indicators for completed years of service, using five years — the minimum required for inclusion in the analytic sample — as the omitted category. Conditional on the labor-group fixed effects (O_i), none of these coefficients is statistically significant (**Table A1**), and a joint test cannot reject the null that they are all equal to zero (p-value = 0.16). The estimates are also small in magnitude. For example, a soldier serving 6 years instead of 5 experiences an additional 0.03 $\mu\text{g}/\text{m}^3$ of PM_{2.5}, which is less than 1% of the mean. This evidence suggests that the instrument affects long-term pollution exposure without systematically altering service duration.

d. The role of other location characteristics

A distinct concern is that soldiers are randomly assigned to locations, not to pollution itself. Even if initial assignment is as good as random within labor groups, more polluted locations may differ from less polluted ones along other dimensions that may also affect health. In that case, our baseline IV specification would recover the effect of pollution bundled together with other location-specific characteristics.

In our setting, this concern is attenuated, though not eliminated, by the fact that the Army standardizes many aspects of soldiers' living and working conditions across bases. Most soldiers live on or near the base, and the Army provides housing, health care access, and other institutional supports in a relatively uniform way across locations. For that reason, many local amenities that complicate civilian pollution estimates may be less important here than in the general population.

Climate conditions remain an important exception. The Army can standardize many features of life across installations, but it cannot equalize climate across locations. Since pollution is correlated with climate, and climate itself can affect morbidity, omitting climate from the baseline specification may confound the estimated effect of pollution. Although one might view instrumenting for climate as a potential solution, this approach

is not feasible in a long-term setting. Any exogenous shock to persistent climate patterns would also affect pollution levels, since pollution is partly determined by atmospheric conditions. In particular, wind-based instruments that generate short-run variation in pollution conditional on climate are not applicable in a setting where the object of interest is cumulative long-term exposure. While it is possible to generate variation in pollution conditional on climate (e.g., through emissions shocks), the converse is not.

We address this concern in two steps. We begin with the parsimonious baseline specification described above, which conditions only on labor-group indicators, and therefore aligns most closely with the assignment-based identification argument. We then estimate parallel specifications that add climate covariates, including average temperature, average precipitation, the number of days below 32°F, and the number of days above 90°F. This comparison is especially informative in our setting because climate is the most salient location characteristic that remains outside the Army's control. **Figure 2** shows that controlling for climate does not meaningfully alter the shape or strength of the first-stage relationship (the F-statistic is 159).

To assess the role of other local amenities, we turn to a broader set of local controls as a sensitivity exercise. Specifically, we examine the robustness of the estimates to a rich set of area-level socioeconomic and health-system characteristics linked to the soldier's assigned zip code. These variables capture demographic composition, labor market conditions, poverty, education, public expenditures, crime, health professional shortages, and measures of health care availability and quality. Because the set of potentially relevant controls is large, we use LASSO to select the subset most predictive of the outcome. This sensitivity analysis is designed to probe our claim above that, apart from climate, other local amenities should not materially affect the estimates in the Army setting, even though soldiers are assigned to places rather than to pollution itself.

A related limitation is that PM_{2.5} is not the only pollutant produced by fossil fuel combustion, and these other pollutants independently affect health. Unfortunately, we do not observe these pollutants at the same spatial and temporal resolution as our satellite-

derived PM_{2.5} measure. The IV estimates reduce concern that the results are driven by sorting into locations with different pollution bundles. However, to the extent that initial PM_{2.5} also shifts exposure to other co-formed pollutants, the IV estimate should be interpreted as the causal effect of the pollution bundle associated with higher long-term PM_{2.5} exposure, rather than the isolated biological effect of PM_{2.5} alone.

V. The effect of long-term pollution exposure on morbidity

We now turn to the estimated effects of long-term PM_{2.5} exposure on morbidity. As described in the previous section, each of our main tables will present two IV estimates, one with and one without controlling for climate variables, in addition to OLS estimates. We focus our attention on the three-diagnosis definition justified earlier, but present results for alternative definitions of morbidity ranging from one to five diagnoses for completeness. We begin with circulatory conditions and then examine respiratory conditions.

a. Reduced form results: initial pollution and long-term morbidity

As a visual preview of our results, **Figure 3** displays binned scatterplots of the reduced-form relationships between the instrument (pollution at the initial location) and health outcomes. Initial PM_{2.5} is positively associated with both circulatory and respiratory conditions, even after controlling for climate. Combined with the tight, linear first-stage relationship shown in **Figure 2**, these figures provide visual support for our main finding that long-term PM_{2.5} exposure increases morbidity, with precise magnitudes recovered in the 2SLS estimates.

b. Effects on circulatory conditions

Panel A of **Table 5** presents our core results for circulatory morbidity. OLS estimates (which simply control for occupation $\times$ skill $\times$ rank $\times$ quarter-of-assignment fixed effects) are negative and statistically insignificant at conventional levels, with t-statistics around

1.5.⁷ The negative estimates imply that soldiers living in areas with higher levels of pollution have fewer circulatory diagnoses, a result contrary to expectations. As previously discussed, however, we suspect bias in the OLS estimates. Even though first year exposure is exogenous given our controls for the labor market group at entry, subsequent moves are likely endogenous, as supported by the lack of covariate balance in later years (shown in **Table 3**). Hence, we focus on our IV estimates for causal interpretation.

Contrary to the OLS estimates, the IV estimates are positive and statistically significant across all diagnostic thresholds. This divergence suggests that failing to account for endogenous location and selection into polluted areas leads OLS to understate the impact of pollution, even in a highly constrained setting like the Army. One plausible explanation is that soldiers with higher human capital sort toward dense, high-amenity areas (Glaeser et al., 2001; Albouy, 2016), consistent with our earlier finding in **Table 3** that higher AFQT scores predict greater pollution exposure among soldiers who serve for many years.

We also compare the IV results with and without controlling for climate. Controlling for climate variables substantially increases the IV estimates for all specifications.

Under the preferred three-diagnosis definition, the climate-controlled IV estimate implies that a one-standard-deviation increase in average PM_{2.5} exposure (1.8 $\mu\text{g}/\text{m}^3$) raises the probability of circulatory morbidity by about 5.5% relative to the mean of 112 cases per 1,000 soldiers. The estimates are robust to how we define having a circulatory condition: they are all positive and statistically significant and they range from 3.8% (if we use only one or more diagnosis) to 6.3% (if we use at least 4 or 5 diagnoses).

⁷ The unconditional correlations between pollution and disease are positive in our sample but they turn negative as soon as time fixed effects are controlled for indicating the positive association is driven by the fact that pollution was higher and health was worse in earlier time periods. But within a given time period and no matter what the controls are, the associations are otherwise negative, as shown in **Table A2**.

Circulatory morbidity encompasses a large and heterogeneous set of conditions, so Panel A of **Table 6** turns to the most common conditions (at the population level) within this category. This disaggregation is useful because, in a relatively young and initially healthy population, some circulatory conditions are more likely to manifest within our observation window than others. The clearest result is for hypertension, for which the IV estimates are positive and statistically significant. The evidence for the other circulatory conditions is weaker, although when climate controls are included, the point estimate for peripheral vascular disease is larger as well, though it remains statistically insignificant. As in the broader circulatory results, adding climate controls increases the magnitudes of the IV coefficients.

The estimated effects on hypertension are economically meaningful. One unit of PM_{2.5} exposure increases hypertension rates by 1.76 cases per 1,000 soldiers when omitting climate controls and 2.46 cases per 1,000 soldiers when including them. A one-standard-deviation increase in average exposure thus raises hypertension prevalence by 4.6 and 6.4% relative to the mean, respectively. These results suggest that hypertension is one important margin along which long-term particulate exposure affects circulatory health.

When we estimate models that include the share of years above the NAAQS threshold value of 9 $\mu\text{g}/\text{m}^3$, shown in **Table 7**, we find that increasing the share from 0 to 1 leads to an additional 17.6 affected soldiers per 1,000 without climate controls and 21.1 with climate controls, with both estimates statistically significant. These estimates imply that experiencing one out of five years above the threshold increases the number of affected soldiers by 3.5 and 4.2 per 1,000 (without and with climate controls, respectively). It is difficult to directly compare to our baseline estimates based on mean PM_{2.5} since the two estimates capture different dimensions of exposure. The mean PM_{2.5} coefficient reflects the effect of a higher average pollution level, while the exceedance coefficient reflects exposure above the NAAQS threshold. The fact that both are positive suggests that morbidity increases both with average pollution intensity and with the persistence of exposure above regulatory standards.

Turning to the cumulative measures of exposure in **Table 7**, whose specifications also control for service length, we find that an additional unit of PM_{2.5} increases circulatory morbidity by 0.22 cases per 1,000 soldiers without climate controls and 0.32 with climate controls. Because the cumulative measure sums annual exposure over a soldier's period of service, we scale these estimates by the average service length of 9.05 years to compare them to the mean-exposure specifications. The resulting estimates, 2.01 and 2.89, are quite similar to the corresponding mean-exposure estimates in the first two columns, 1.95 and 2.94, respectively. Applying the same exercise to the threshold measures in columns (7) and (8) yields a similar conclusion. Taken together, these results suggest that differential service length across soldiers is not driving our results.

c. Respiratory Conditions

Panel B of **Table 5** presents our core results for respiratory morbidity. As with circulatory disease, the OLS and IV estimates differ in sign, with the IV estimates uniformly positive. In contrast to the circulatory results, however, the respiratory estimates are not statistically significant across diagnostic thresholds, regardless of whether climate controls are included, and smaller in magnitude. Using the 3+ classification and the IV coefficient that controls for climate, a one-standard-deviation increase in average PM_{2.5} exposure implies a 1.3% increase in respiratory morbidity, with estimates ranging from less than 1% to 2% across outcome definitions.

Panel B of **Table 6** unpacks the broad respiratory category by examining the four most common population-level diagnoses. As with circulatory conditions, this breakdown is useful in a relatively young and initially healthy population, where some respiratory conditions are more likely to manifest within our observation window than others. Consistent with this logic we find a statistically significant relationship for asthma as well as influenza and pneumonia, though only when climate controls are included.⁸

⁸ While influenza and pneumonia may seem like less obvious long-term outcomes, two mechanisms could explain this finding. First, sustained PM_{2.5} exposure may gradually impair immune function and respiratory

To put these coefficients in context, a one-unit increase in average PM_{2.5} exposure implies an increase of 1.23 asthma cases per 1,000 soldiers, or roughly 4.3% relative to the mean. The corresponding estimate for influenza/pneumonia is 0.98 cases per 1,000 soldiers, or roughly 5.8% relative to the mean. A one-standard-deviation increase in average PM_{2.5} exposure is associated with roughly a 7% increase in asthma prevalence and a 10% increase in the prevalence of influenza and pneumonia. These results should be interpreted with caution given their sensitivity to climate controls. Still, the pattern is broadly consistent with long-term particulate exposure affecting respiratory conditions that are more likely to appear within our observation window.

Table 7 provides a similar picture using alternative exposure measures. For aggregate respiratory morbidity, neither the NAAQS-based measures nor cumulative exposure yields statistically significant estimates. At the diagnosis level, however, cumulative exposure produces statistically significant increases in asthma and influenza/pneumonia when climate controls are included. The NAAQS-based estimates point in the same direction, but are only marginally significant. Overall, these results point to weaker respiratory effects than circulatory effects, with the strongest evidence appearing in the disaggregated asthma and influenza/pneumonia outcomes rather than in aggregate respiratory morbidity.

d. Robustness checks

Our climate controls address the most immediate concern raised by the fact that soldiers are assigned to places rather than to pollution itself. **Table 8** asks whether the results are also sensitive to a much richer set of area-level controls. In all specifications, we continue to control for climate and then use the LASSO IV procedure of Chernozhukov, Hansen,

defenses, leaving soldiers permanently more susceptible to acute infections. Second, soldiers in more polluted environments may experience more frequent pollution-infection interactions over their careers, with our measure capturing the cumulative incidence of repeated acute infections. Both channels are consistent with recent evidence that pollution exposure exacerbates respiratory infections, including influenza (Graff Zivin et al., 2023).

and Spindler (2015) to select from increasingly broad sets of county- and hospital-referral-region-level characteristics. These include measures of health professional shortages, labor market conditions, county typology and rurality, federal and local expenditures, crime, and Medicare-based measures of mortality, reimbursement, and preventive care.

The circulatory results are highly stable across these specifications. The 2SLS coefficient remains tightly clustered, ranging from 2.7 to 4.0 cases per 1,000 soldiers, despite allowing LASSO to choose among increasingly large sets of potential controls. The estimates also remain precise, although the richest specification (in column 10) falls just short of conventional significance thresholds. This stability suggests that, once climate is accounted for, adding a broad set of local socioeconomic and health-system characteristics does little to change the estimated effect of long-term pollution exposure on circulatory morbidity.

The respiratory results tell a similar, though weaker, story. The 2SLS coefficients remain positive but statistically insignificant across all LASSO specifications, ranging from 1.5 to 3.7 cases per 1,000 soldiers. Thus, the absence of a precisely estimated broad respiratory effect is itself robust to the inclusion of a rich set of local controls.

The overall pattern of results shown in **Table 8** provides additional reassurance that, once climate is accounted for, the remaining variation tells us about pollution rather than place. For circulatory morbidity, the positive 2SLS effect survives the inclusion of a much broader control set with little movement in magnitude. For respiratory morbidity, the broad null remains unchanged.

e. Interpreting IV coefficients

Interpreting the 2SLS estimates as a weighted average of causal responses among soldiers whose exposure is shifted by the instrument requires a monotonicity assumption that initial assignment to a higher pollution location does not reduce an individual's long-term pollution exposure. In this setting, a violation would arise if soldiers initially assigned to higher pollution locations were systematically reassigned to cleaner locations or exited

service earlier in ways that reduced their cumulative exposure relative to soldiers initially assigned to lower pollution locations. While this assumption is not directly testable, we provide three pieces of evidence to assess its plausibility.

First, the dynamic first stage results shown in **Figure 1**, which indicate that higher initial pollution predicts not only higher cumulative exposure over time but also higher pollution exposure in each individual year, suggesting initial assignment to higher pollution locations does not systematically lead to reassignment to cleaner postings. Second, as shown in **Table A1**, initial pollution assignment is unrelated to length of service and thus probability of exit from the Army. Third, we find a nearly linear relationship between initial pollution and long-term pollution as shown in **Figure 2**. These three results are consistent with a monotone relationship between initial assignment and long-term exposure.

f. Short- and long-term effects

As noted above, our sample is unusually healthy at enrollment, since good health is a condition for enlistment in the Army. Short-term pollution exposure is generally thought to affect more medically vulnerable populations — such as the very young, the elderly, or those with underlying comorbidities. We therefore would not expect to find strong short-run effects on health outcomes in our setting, a prediction we can test directly.

To examine shorter-run effects, we construct a sample of soldiers whose health outcomes are observed within 180 to 540 days after the start of service. This window is substantially shorter than the cumulative exposure window in our main analysis, though still longer than the acute day-to-day variation typically studied in the epidemiological literature. Comparing these estimates with our main results helps assess whether chronic conditions begin to emerge after limited exposure or instead require a longer period of accumulation.

Table 9 shows that exposure of less than two years does not have a statistically significant effect on chronic circulatory or respiratory morbidity in our sample. The corresponding

coefficients are also substantially smaller than those in the main specifications, a pattern consistent with duration of exposure being an important component of the long-term health effects we estimate. Because this exercise changes both the sample and the outcome window, we read it as consistent with, rather than as identifying, a longer exposure duration is necessary for uncovering an impact on health. To be clear, this exercise varies the duration of exposure rather than its volatility: the endogenous variable remains assignment-induced average PM_{2.5}, now measured over a shorter window. The null therefore concerns short-duration exposure and is not evidence of the acute effects of day-to-day pollution fluctuations.

Since we follow soldiers for an average of 9 years, we can also explore the specific impacts from even longer-term exposure. **Table 10** further examines how the 2SLS estimates vary with duration of service among soldiers who serve longer than five years. Although the sample size declines as we restrict attention to soldiers with longer service histories, the estimated circulatory effect remains positive and statistically significant for durations up to eight years, after which the coefficients remain comparable in magnitude but lose statistical significance. Each successive restriction yields a more selected sample, so we interpret this stability as evidence that the circulatory effect is not confined to the shortest-serving soldiers rather than as a dose-response in duration.

g. Exploring effects on other outcomes

The analysis so far has centered on circulatory and respiratory morbidity — two categories most directly linked to PM_{2.5} based on the prior literature. This focus raises two related questions: whether pollution affects other conditions not yet examined, and whether conditions with no plausible link to pollution serve as credible placebos. Since PM_{2.5} has been associated with a wide range of outcomes, it is difficult to classify conditions *ex ante* as signal or placebo. We therefore estimate the effect of pollution on 100 specific conditions (based on their prevalence in the general population) and report the empirical distribution of these estimates, scaled by disease prevalence to make them comparable across conditions. **Figure 4** shows that hypertension ranks seventh and asthma third among all conditions by estimated effect size. The prominence of two conditions with well-

established biological links to particulate exposure at the top of this distribution is unlikely to reflect diagnostic intensity alone and provides additional support for a causal interpretation of our main results.

VI-Conclusion

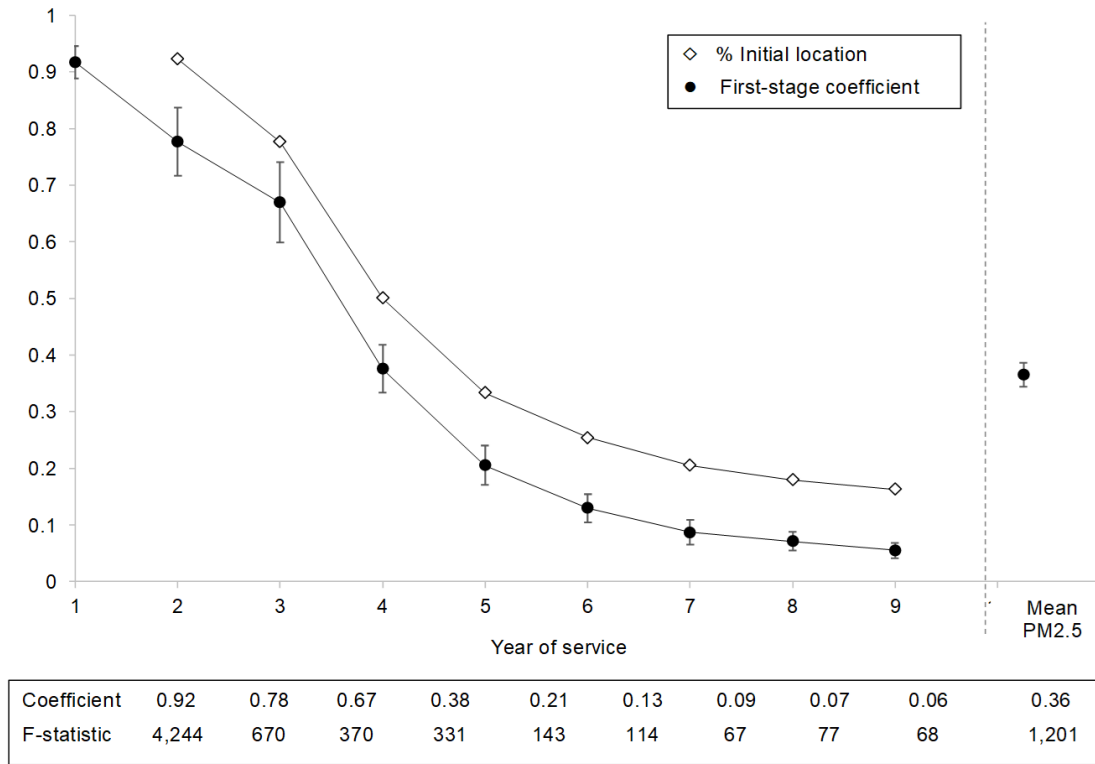
This paper provides novel causal evidence that long-term exposure to PM_{2.5} at contemporary ambient levels contributes to the development of chronic disease. Exploiting quasi-random assignment of soldiers to locations within the U.S. Army, we show that sustained pollution exposure increases circulatory morbidity in an initially healthy population. The broad circulatory results are robust across alternative coding rules, and the strongest and most consistent diagnosis-level effect is on hypertension. Respiratory results are weaker at the aggregate level, but the disaggregated estimates point to asthma and influenza/pneumonia as the specific margins along which long-term exposure may affect respiratory health. More broadly, these results help distinguish the consequences of long-term exposure from the acute effects emphasized in much of the existing literature, and they show that sustained exposure to pollution can produce measurable chronic disease even in a population of relatively young adults who begin from an unusually healthy baseline.

The diagnoses that move in our data are not minor endpoints. Hypertension is a major modifiable risk factor for later cardiovascular disease, including coronary heart disease, stroke, and heart failure. Evidence from young adult cohorts shows that elevated blood pressure early in life can more than double the risks of developing these cardiovascular diseases (Robinson et al., 2024; Rietz et al., 2023). The respiratory evidence is more qualified, but points to conditions that are also consequential. Asthma is a persistent disease with links to later COPD and cardiovascular morbidity (Asamoah-Boaheng et al., 2018; Zhang et al., 2022), while influenza and pneumonia may reflect weakened respiratory defenses or repeated pollution-infection interactions over time. Viewed in that light, our findings point to the early onset of conditions that can foreshadow more serious disease later in life.

These findings also sharpen the policy stakes. We estimate adverse health effects at contemporary U.S. ambient concentrations, with mean exposure in our sample below the current annual $\text{PM}_{2.5}$ standard, and we do so in a population that is younger, healthier, and more uniformly insured than the general public. If sustained exposure shifts chronic morbidity in this setting, then the corresponding burden in the broader population is likely larger. At the same age, the civilian population is less healthy and has worse access to health care services. The military context gives the paper strong internal validity, but the broader implication is straightforward: policies that focus primarily on pollution spikes or mortality miss an important part of the welfare cost of air pollution — its role in gradually producing chronic disease over the life course. Obtaining causal estimates for the civilian settings is an important next step toward understanding population-level impacts and improving optimal policy design.

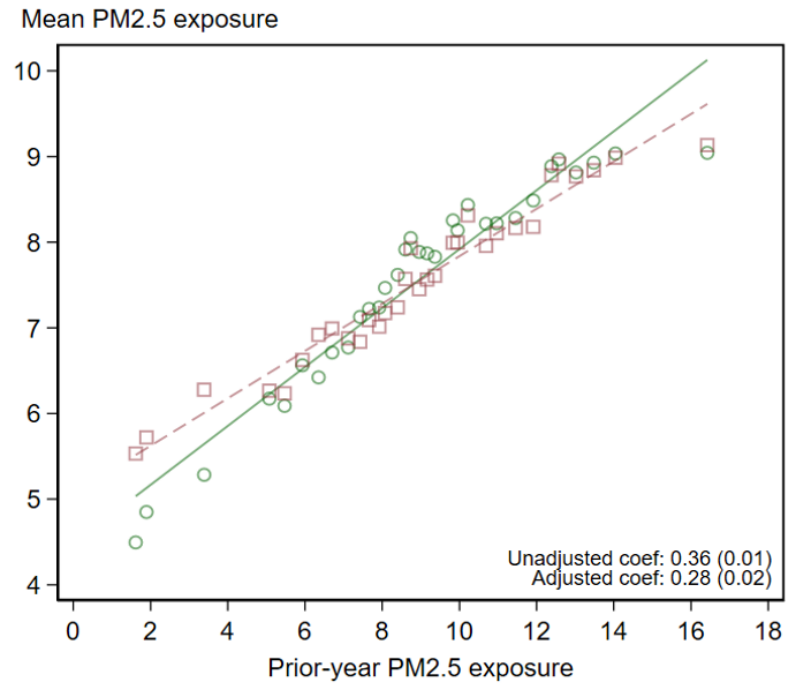
VII-Figures

Figure 1. Persistence of Initial Duty-Station Assignment and PM2.5 Exposure Across Service Years



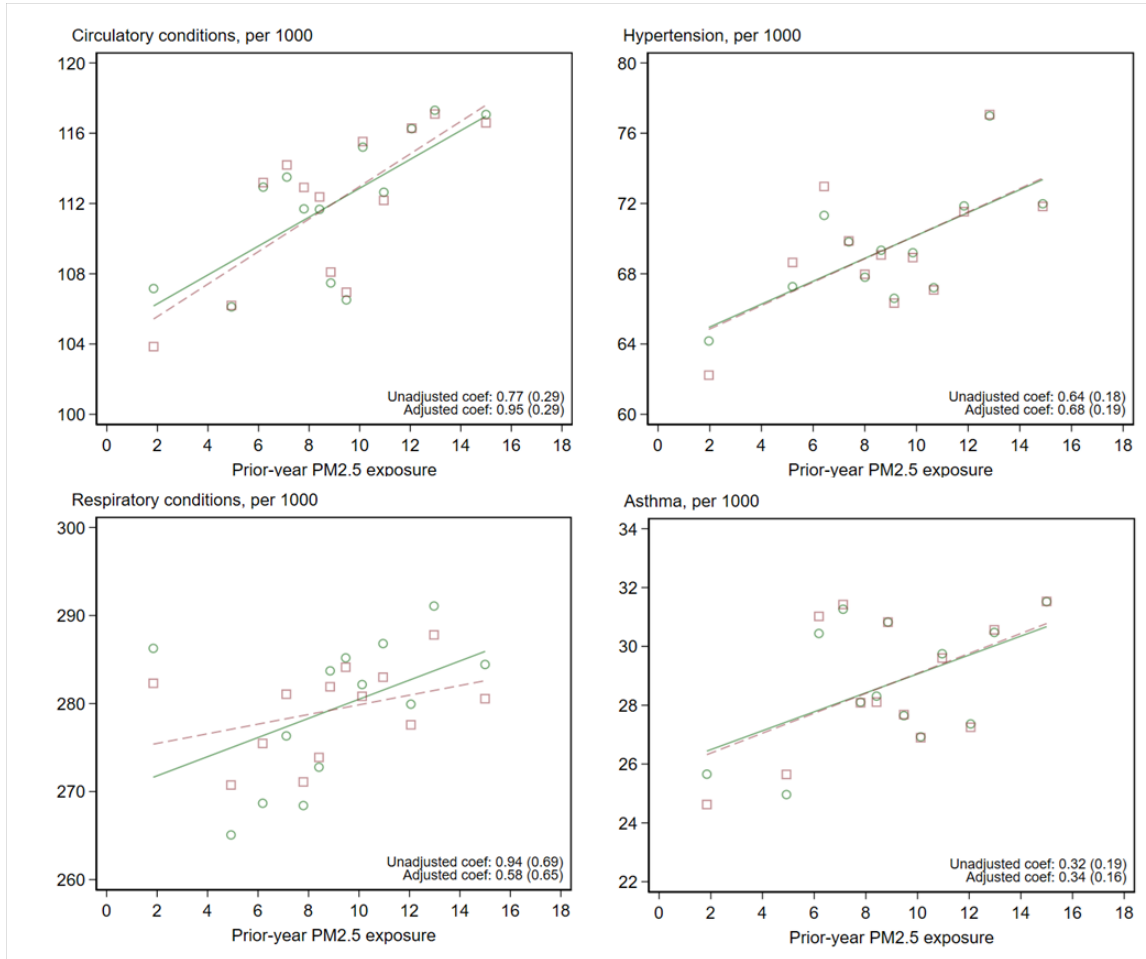
Notes: The figure shows the persistence of initial duty-station assignments and the relationship between prior-year and subsequent PM2.5 exposure over soldiers' years of service. Diamonds indicate the proportion of soldiers whose assigned duty station remains the same as their initial duty station in each service year. Circles report coefficients from separate regressions of PM2.5 exposure in service years 1-9 on prior-year exposure; vertical bars indicate 95% confidence intervals. "Mean PM2.5" is from a regression of average exposure across all observed service years on prior-year exposure. Coefficients and corresponding first-stage F-statistics are reported below the figure. All models include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects. Standard errors are clustered at the duty-station level.

Figure 2. First-Stage Relationship with Prior-Year Exposure



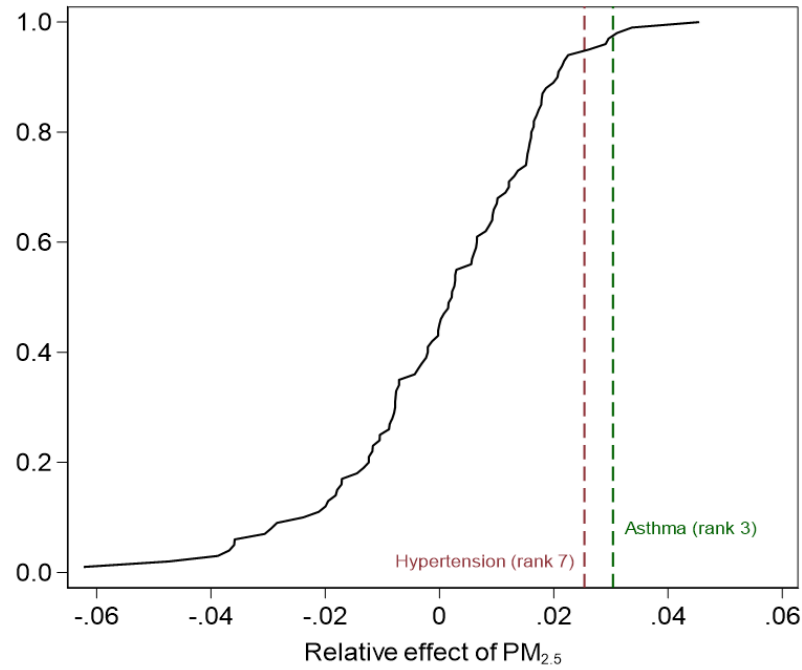
Notes: The figure presents binned scatterplots of the relationships between prior-year PM2.5 exposure and subsequent pollution exposure. Bins are constructed using the data-driven methods of Cattaneo et al. (2024), with the number of bins selected to minimize integrated mean squared error. The solid green series adjusts for primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects but does not control for climate variables. The dashed red series additionally controls for climate variables. Regression coefficients are reported within each panel, with standard errors in parentheses.

Figure 3. Reduced-Form Relationships with Prior-Year Exposure



Notes: The figure presents binned scatterplots of the relationships between prior-year PM2.5 exposure and health outcomes. The panels show reduced-form relationships between prior-year exposure and circulatory conditions, hypertension, respiratory conditions, and asthma, reported per 1,000 soldiers. Bins are constructed using the data-driven methods of Cattaneo et al. (2024), with the number of bins selected to minimize integrated mean squared error. The solid green series adjusts for primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects but does not control for climate variables. The dashed red series additionally controls for climate variables. Regression coefficients are reported within each panel, with standard errors in parentheses.

Figure 4. Relative Effects of PM_{2.5} Across 100 Comparison Conditions



Notes: The figure plots the empirical cumulative distribution function of estimated relative effects of PM_{2.5} exposure across 100 non-circulatory and non-respiratory conditions that are common among individuals of similar age to soldiers in our sample. For each condition, the relative effect is calculated as the 2SLS estimate of the effect of average exposure on condition prevalence divided by the mean prevalence of that condition in the analytic sample. The vertical dashed lines indicate the estimated relative effects for hypertension and asthma. Hypertension ranks seventh and asthma ranks third among the 100 comparisons. All specifications include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects.

VIII-Tables

Table 1. Characteristics of Soldiers in the Analytical Sample

	Mean	SD
Age, initial year	22.0	3.73
Age, in 2015	27.6	5.57
Service length (years)	9.05	4.01
Pay grade, initial year		
E01	0.01	0.08
E02	0.29	0.45
E03	0.66	0.47
E04	0.05	0.21
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 ($\mu\text{g}/\text{m}^3$) exposure		
Year prior to initial year	8.9	3.4
Initial year	8.6	3.2
Average over service	7.5	1.8
Soldiers	148,681	

Notes: The table reports means and standard deviations for soldiers included in the primary analytic sample (N = 148,681). The initial year is defined as the fiscal year of a soldier's first assignment following Army basic training. Individual characteristics are measured at the time of the initial assignment, except for length of service, which is measured as the total number of years from the initial assignment through discharge, and age in 2015, which is measured at the beginning of the health outcomes observation period. AFQT denotes the Armed Forces Qualification Test, with "1" being the highest category. PM2.5 exposure is measured at the ZIP-code level.

Table 2. Prevalence of Circulatory and Respiratory Conditions

	Diagnoses, per 1000 soldiers					
	Count	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Circulatory conditions	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 conditions	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 conditions are identified from diagnosis codes recorded in Army medical claims between 2015 and 2020, including inpatient and outpatient encounters delivered both on and off base. All values are reported per 1,000 soldiers. The first numeric column reports the total number of diagnosis claims per 1,000 soldiers. The remaining columns report the number of soldiers per 1,000 with at least the indicated number of diagnoses for a given condition during the study period. ICD-9-CM and ICD-10-CM codes used to define each condition are provided in the Appendix.

Table 3. Covariate Balance in PM2.5 Exposure by Service Year

	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 (0.003)	0.001 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.007 (0.004)	-0.006 (0.004)	-0.003 (0.001)
Black	0.112 (0.067)	0.095 (0.061)	0.122 (0.070)	0.187 (0.062)	0.337 (0.052)	0.391 (0.049)	0.230 (0.038)
Hispanic	-0.032 (0.042)	-0.026 (0.045)	-0.020 (0.049)	-0.016 (0.044)	-0.017 (0.039)	-0.029 (0.029)	0.021 (0.028)
Male	0.015 (0.065)	0.021 (0.059)	0.056 (0.067)	0.035 (0.062)	0.011 (0.043)	-0.002 (0.031)	-0.058 (0.035)
Single	-0.134 (0.098)	-0.115 (0.092)	-0.121 (0.093)	-0.085 (0.078)	-0.016 (0.042)	0.036 (0.031)	-0.034 (0.044)
AFQT 1-3A	0.053 (0.046)	0.056 (0.043)	0.042 (0.042)	0.088 (0.039)	0.124 (0.041)	0.127 (0.039)	0.102 (0.024)
High school graduate only	-0.039 (0.032)	-0.042 (0.031)	-0.017 (0.033)	0.001 (0.033)	0.004 (0.027)	-0.010 (0.028)	-0.009 (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 estimates from a separate regression of PM2.5 exposure on individual characteristics. Exposure is measured during the year preceding the initial assignment, the initial assignment year, each of the following five years, and as the individual's mean exposure over the observed service period. All models include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects. Standard errors, clustered at the duty-station level, are reported in parentheses. The F-statistic and corresponding p-value test the joint null hypothesis that the coefficients on all listed individual characteristics equal zero.

Table 4. Covariate Balance Across Initial Duty Stations

	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 ≤ 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 estimates from a separate regression of the indicated individual characteristic on a set of initial-duty-station indicators. "Aberdeen" is the omitted reference station. Each station coefficient represents the adjusted difference in the characteristic relative to soldiers initially assigned to Aberdeen. All models include primary military occupational specialty × skill qualification identifier × pay grade × assignment-quarter fixed effects. The F-statistic tests the joint null hypothesis that all initial-duty-station coefficients equal zero. The randomization-inference p-value is based on 1,000 simulated reassignments of soldiers to initial duty stations and reports the proportion of simulated F-statistics that are at least as large as the observed F-statistic.

Table 5. Effects of PM2.5 Exposure on Circulatory and Respiratory Health

	Diagnoses, per 1000 soldiers				
	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Panel A: Circulatory conditions					
Mean	211	142	112	93	79
OLS	-1.77 (1.18)	-1.49 (0.99)	-1.36 (0.82)	-1.14 (0.78)	-1.08 (0.69)
2SLS	3.18 (1.17)	2.73 (0.98)	2.12 (0.82)	2.06 (0.63)	1.60 (0.67)
2SLS, climate controls	4.40 (1.66)	4.19 (1.30)	3.39 (1.15)	3.24 (1.04)	2.75 (0.94)
Panel B: Respiratory conditions					
Mean	551	379	279	216	173
OLS	-5.37 (2.52)	-2.74 (2.07)	-1.08 (1.80)	-0.71 (1.73)	-0.33 (1.53)
2SLS	2.45 (1.52)	1.97 (2.07)	2.58 (1.91)	2.48 (1.84)	2.00 (1.75)
2SLS, climate controls	2.23 (3.61)	1.17 (2.74)	2.09 (2.31)	2.64 (1.99)	1.72 (1.58)

Notes: The table reports ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the relationship between average PM2.5 exposure and circulatory and respiratory conditions. Outcomes are the number of soldiers per 1,000 with at least the indicated number of diagnoses. The outcome mean is reported. Coefficients represent the change in the outcome rate per 1,000 soldiers associated with a 1- $\mu\text{g}/\text{m}^3$ increase in average exposure. All specifications include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects. The OLS specifications regress each outcome on average exposure. The 2SLS specifications instrument for average exposure using prior-year exposure. The specifications “2SLS, climate controls” additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

Table 6. Effects of PM2.5 Exposure on Circulatory and Respiratory Diagnoses

	≥ 3 diagnoses, per 1000 individuals			
	Mean	OLS	2SLS	2SLS, climate controls
Panel A: Circulatory conditions	112	-1.36 (0.82)	2.12 (0.82)	3.39 (1.15)
Hypertension	69	-0.60 (0.64)	1.76 (0.52)	2.46 (0.78)
Peripheral vascular disease	4.4	-0.02 (0.13)	0.20 (0.22)	0.42 (0.28)
Coronary artery disease	5.2	-0.13 (0.10)	-0.13 (0.17)	-0.18 (0.29)
Heart failure	1.4	-0.01 (0.06)	0.01 (0.09)	0.06 (0.14)
Panel B: Respiratory conditions	279	-1.08 (1.80)	2.58 (1.91)	2.09 (2.31)
Chronic obstructive pulmonary disease	5.7	0.13 (0.15)	0.09 (0.21)	0.07 (0.30)
Asthma	29	0.24 (0.36)	0.87 (0.54)	1.23 (0.59)
Acute upper respiratory infection	139	-1.10 (1.12)	0.41 (1.56)	0.48 (2.11)
Influenza and pneumonia	17	-0.01 (0.28)	0.47 (0.39)	0.98 (0.46)

Notes: The table reports ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the relationship between average PM2.5 exposure and circulatory and respiratory conditions. Outcomes are measured as the number of soldiers per 1,000 with at least 3 diagnoses. Coefficients represent the change in the outcome rate per 1,000 soldiers associated with a 1- $\mu\text{g}/\text{m}^3$ increase in average exposure. All specifications include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects. The OLS specifications regress each outcome on average exposure. The 2SLS specifications instrument for average exposure using prior-year exposure. The specifications “2SLS, climate controls” additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

Table 7. Effects of Alternative Measures of PM2.5 Exposure on Circulatory and Respiratory Conditions

	Average exposure		Cumulative exposure		Share of years > 9µg/m³		Number of years > 9µg/m³	
	2SLS	2SLS, climate controls	2SLS	2SLS, climate controls	2SLS	2SLS, climate controls	2SLS	2SLS, climate controls
Panel A: Circulatory conditions	1.95 (0.80)	2.94 (1.22)	0.22 (0.09)	0.32 (0.13)	17.64 (7.56)	21.06 (9.56)	1.98 (0.85)	2.33 (1.05)
Hypertension	1.64 (0.51)	2.15 (0.77)	0.19 (0.06)	0.23 (0.08)	14.84 (5.04)	15.41 (6.15)	1.67 (0.56)	1.71 (0.67)
Peripheral vascular disease	0.19 (0.22)	0.40 (0.29)	0.02 (0.03)	0.04 (0.03)	1.76 (2.01)	2.87 (2.12)	0.20 (0.23)	0.32 (0.23)
Coronary artery disease	-0.14 (0.17)	-0.21 (0.30)	-0.02 (0.02)	-0.02 (0.03)	-1.28 (1.56)	-1.48 (2.13)	-0.14 (0.17)	-0.16 (0.24)
Heart failure	0.01 (0.09)	0.06 (0.14)	0.00 (0.01)	0.01 (0.01)	0.08 (0.84)	0.45 (0.95)	0.01 (0.10)	0.05 (0.11)
Panel B: Respiratory conditions	2.15 (1.76)	0.78 (1.83)	0.25 (0.20)	0.08 (0.20)	19.49 (14.11)	5.60 (13.27)	2.19 (1.57)	0.62 (1.47)
Chronic obstructive pulmonary disease	0.08 (0.21)	0.04 (0.31)	0.01 (0.02)	0.00 (0.03)	0.77 (1.90)	0.31 (2.19)	0.09 (0.22)	0.03 (0.24)
Asthma	0.82 (0.53)	1.11 (0.58)	0.09 (0.06)	0.12 (0.06)	7.47 (5.05)	7.98 (4.46)	0.84 (0.56)	0.88 (0.49)
Acute upper respiratory infection	0.20 (1.50)	-0.24 (1.93)	0.02 (0.17)	-0.03 (0.21)	1.78 (13.45)	-1.75 (13.77)	0.20 (1.51)	-0.19 (1.53)
Influenza and pneumonia	0.44 (0.38)	0.89 (0.46)	0.05 (0.04)	0.10 (0.05)	4.02 (3.30)	6.39 (3.42)	0.45 (0.37)	0.71 (0.37)
Mean		7.54		70.1		0.27		2.70
Standard deviation		1.85		40.0		0.27		3.02

Notes: The table reports two-stage least squares (2SLS) estimates of the relationships between alternative measures of PM2.5 exposure and circulatory and respiratory conditions. Each outcome is defined as the number of soldiers per 1,000 with at least three diagnoses for the indicated condition. Average exposure is the mean annual exposure across a soldier's observed years of service. Cumulative exposure is the sum of annual exposure across observed service years. The share-above-threshold measure is the proportion of observed service years in which annual average exposure exceeded 9 µg/m³. The number-above-threshold measure is the total number of observed service years in which annual average exposure exceeded 9 µg/m³. Each exposure measure is instrumented using prior-year PM2.5 exposure. All specifications include indicators for years of service and primary military occupational specialty × skill qualification identifier × pay grade × assignment-quarter fixed effects. Specifications "2SLS, climate controls" additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

Table 8. Sensitivity to LASSO-Selected Geographic Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Circulatory conditions, ≥ 3 diagnoses										
2SLS	3.39 (1.08)	3.25 (1.45)	3.52 (1.39)	3.02 (1.34)	3.46 (1.42)	3.46 (1.42)	2.68 (1.24)	2.72 (1.24)	4.00 (1.66)	2.78 (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 (2.18)	1.59 (2.86)	1.58 (2.75)	1.76 (2.76)	1.46 (2.80)	1.46 (2.80)	3.62 (2.41)	3.70 (2.42)	2.24 (3.56)	2.70 (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
<i>Required controls</i>										
Climate	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
<i>Potential controls</i>										
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 two-stage least squares (2SLS) estimates of the effect of average PM2.5 exposure on circulatory and respiratory conditions. Outcomes are measured as the number of soldiers per 1,000 with at least three diagnoses. Average exposure is instrumented using prior-year exposure. Column (1) reports the baseline specification. Columns (2)-(10) use the partialling-out LASSO instrumental-variables procedure described by Chernozhukov, Hansen, and Spindler (2015). Across columns, the set of potential geographic controls available for LASSO selection expands cumulatively. “Number of potential controls” and “Number of selected controls” report the number of candidate variables available and the number selected by LASSO, respectively. All specifications include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects and climate controls. Standard errors, clustered at the duty-station level, are reported in parentheses. Standard errors in column (1) are narrower than those the primary estimates because LASSO applies the Frisch-Waugh-Lovell partialling-out procedure to the labor-group fixed effects within the 2SLS estimation.

Table 9. Effects of PM2.5 Exposure on Short-Term Health

	Diagnoses, per 1000 soldiers				
	≥ 1	≥ 2	≥ 3	≥ 4	≥ 5
Panel A: Circulatory conditions					
Mean	73	42	29	23	18
2SLS	1.52 (0.99)	-0.71 (0.99)	-0.78 (1.03)	-0.45 (0.95)	-0.33 (0.77)
2SLS, climate controls	1.36 (0.77)	0.02 (0.88)	0.23 (0.86)	0.34 (0.74)	0.39 (0.61)
Panel B: Respiratory conditions					
Mean	521	312	196	130	90
2SLS	2.29 (2.91)	3.12 (2.02)	3.10 (1.63)	0.82 (1.92)	0.35 (1.55)
2SLS, climate controls	-1.80 (2.77)	-0.03 (2.62)	1.82 (1.74)	0.40 (1.97)	0.88 (1.52)
Soldiers	47,311				

Notes: The table reports two-stage least squares (2SLS) estimates of the relationship between average PM2.5 exposure and short-term circulatory and respiratory outcomes. Health outcomes are measured during the period from 180 through 540 days after each soldier's initial assignment date. Outcomes are expressed as the number of soldiers per 1,000 with at least the indicated number of diagnoses during this observation window. Coefficients represent the change in the outcome rate per 1,000 soldiers associated with a 1- $\mu\text{g}/\text{m}^3$ increase in average exposure. The 2SLS specifications instrument for average exposure using prior-year exposure. All specifications include primary military occupational specialty $\times$ skill qualification identifier $\times$ pay grade $\times$ assignment-quarter fixed effects. Specifications "2SLS, climate controls" additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

Table 10. Sensitivity of Estimated PM_{2.5} Effects to Minimum Length of Service

	Minimum length of service, years					
	≥ 5	≥ 6	≥ 7	≥ 8	≥ 9	≥ 10
Circulatory conditions, ≥ 3 diagnoses						
Mean	112	123	136	149	161	172
2SLS	2.12 (0.82)	2.70 (1.06)	3.11 (1.21)	3.28 (1.32)	3.23 (1.80)	2.92 (2.51)
2SLS, climate controls	3.39 (1.15)	3.98 (1.36)	4.24 (1.76)	4.11 (1.69)	4.15 (2.14)	3.62 (2.82)
Respiratory conditions, ≥ 3 diagnoses						
Mean	279	291	304	319	333	344
2SLS	2.58 (1.91)	2.53 (1.71)	2.33 (1.52)	2.58 (1.95)	1.05 (2.39)	0.74 (2.92)
2SLS, climate controls	2.09 (2.31)	0.83 (2.67)	0.51 (3.15)	1.04 (3.69)	-0.40 (4.05)	-0.87 (4.23)
Soldiers	148,681	120,458	95,795	77,568	63,246	51,494

Notes: The table reports two-stage least squares (2SLS) estimates of the relationship between average PM_{2.5} exposure and circulatory and respiratory conditions. Each outcome is defined as the number of soldiers per 1,000 with at least three diagnoses. Coefficients represent the change in the outcome rate per 1,000 soldiers associated with a 1-μg/m³ increase in average exposure. Columns restrict the analytic sample to soldiers who served for at least the indicated number of years. Average PM_{2.5} exposure is instrumented using prior-year exposure. All specifications include primary military occupational specialty × skill qualification identifier × pay grade × assignment-quarter fixed effects. Specifications “2SLS, climate controls” additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

References

- Abadie, Alberto. "Bootstrap tests for distributional treatment effects in instrumental variable models." *Journal of the American Statistical Association* 97, no. 457 (2002): 284-292.
- Albouy, D. (2016). What are cities worth? Land rents, local productivity, and the total value of amenities. *Review of Economics and Statistics*, 98(3), 477–487.
- Alfano R, Herceg Z, Nawrot TS, Chadeau-Hyam M, Ghantous A, Plusquin M (2018) The impact of air pollution on our epigenome: how far is the evidence? (A Systematic Review). *Curr Environ Health Rep* 5(4):544–578.
- Anderson, M. L. (2020). As the wind blows: The effects of long-term exposure to air pollution on mortality. *Journal of the European Economic Association*, 18(4), 1886-1927.
- Asamoah-Boaheng M, Acheampong L, Tenkorang EY, Farrell J, Oyet A, Midodzi WK. Association between early history of asthma and COPD diagnosis in later life: a systematic review and meta-analysis. *Int J Epidemiol*. 2018 Dec 1;47(6):1865-1876.
- Banzhaf, H. Spencer, and Randall P. Walsh (2008). "Do People Vote with Their Feet? An Empirical Test of Tiebout." *American Economic Review*, 98 (3): 843-63.
- Barreca, A. I., Neidell, M., & Sanders, N. J. (2021). Long-term pollution exposure and mortality: Evidence from the Acid Rain Program. *Journal of Public Economics*, 200, 104440.
- Barzegari Banadkooki, F. (2025). The impact of air pollution on mental health: Evidence from Texas. *Journal of Environmental Economics and Management*, 132, 103134.
- Beelen, R., Raaschou-Nielsen, O., Stafoggia, M., Andersen, Z. J., Weinmayr, G., Hoffmann, B., ... & Hoek, G. (2014). Effects of long-term exposure to air pollution on natural-cause mortality: an analysis of 22 European cohorts within the multicentre ESCAPE project. *The lancet*, 383(9919), 785-795.
- Birman-Deych, Elena, Amy D. Waterman, Yan Yan, David S. Nilasena, Martha J. Radford, and Brian F. Gage. "Accuracy of ICD-9-CM codes for identifying cardiovascular and stroke risk factors." *Medical care* 43, no. 5 (2005): 480-485.
- Brook, R. D., Rajagopalan, S., Pope III, C. A., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., ... & Kaufman, J. D. (2010). Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation*, 121(21), 2331-2378.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., ... & Zhang, A. T. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, 137(4), 2037-2105.

Carter, S. P., & Skimmyhorn, W. (2017). Much ado about nothing? New evidence on the effects of payday lending on military members. *Review of Economics and Statistics*, 99(4), 606-621.

Carter, S. P., & Wozniak, A. (2023). Making big decisions: The impact of moves on marriage among US army personnel. *Journal of Human Resources*, 58(3), 713-754.

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3), 141-169.

Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences*, 110(32), 12936-12941.

Chernozhukov, V., Hansen, C., & Spindler, M. (2015). Post-selection and post-regularization inference in linear models with many controls and instruments. *American Economic Review*, 105(5), 486-490.

Coates, Jane, et al. "The influence of temperature on ozone production under varying NO_x conditions—a modelling study." *Atmospheric Chemistry and Physics* 16.18 (2016): 11601-11615.

Council for a Strong America. (2023). "Retired Military Leaders Sound Alarm on New Data Showing Massive Rate of Military Ineligibility among American Youth." *Strong Nation*.

Crouse, D. L., Peters, P. A., Hystad, P., Brook, J. R., van Donkelaar, A., Martin, R. V., ... & Burnett, R. T. (2015). Ambient PM_{2.5}, O₃, and NO₂ exposures and associations with mortality over 16 years of follow-up in the Canadian Census Health and Environment Cohort (CanCHEC). *Environmental health perspectives*, 123(11), 1180.

Currie, J., Voorheis, J., & Walker, R. (2023). What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality. *American Economic Review*, 113(1), 71-97.

Department of Defense Instruction 1145.01 (2013) Qualitative Distribution of Military Manpower. Office of the Under Secretary of Defense for Personnel and Readiness.

Department of War Instruction 6130.03, Volume 1 (2018) Medical Standards for Military Service: Appointment, Enlistment, or Induction. Office of the Under Secretary of War for Personnel and Readiness.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12), 4178-4219.

Deryugina, T., & Reif, J. (2023). *The long-term effect of air pollution on survival* (No. w31858). National Bureau of Economic Research.

Deschênes, Olivier, and Michael Greenstone. "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US." *American Economic Journal: Applied Economics* 3.4 (2011): 152-185.

Deschenes, O., Wang, H., Wang, S., & Zhang, P. (2020). The effect of air pollution on body weight and obesity: Evidence from China. *Journal of Development Economics*, 145, 102461.

De Silva, D. G., Schiller, A. R., Slechten, A., & Wolk, L. (2024). Tiebout sorting and toxic releases. *Environmental and Resource Economics*, 87(9), 2487-2520.

Di, Q., Wang, Y., Zanobetti, A., Wang, Y., Koutrakis, P., Choirat, C., ... & Schwartz, J. D. (2017). Air pollution and mortality in the Medicare population. *New England Journal of Medicine*, 376(26), 2513-2522.

Dockery, D. W., Pope, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., ... & Speizer, F. E. (1993). An association between air pollution and mortality in six US cities. *New England Journal of medicine*, 329(24), 1753-1759.

Dominici, F., McDermott, A., Zeger, S. L., & Samet, J. M. (2003). Airborne particulate matter and mortality: timescale effects in four US cities. *American Journal of Epidemiology*, 157(12), 1055-1065.

Ebenstein, A., Fan, M., Greenstone, M., He, G., & Zhou, M. (2017). New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proceedings of the National Academy of Sciences*, 114(39), 10384-10389.

Finney, M., Goetzke, F., & Yoon, M. (2011). "Income Sorting and the Demand for Clean Air: Evidence from Southern California." *Land Economics*, 87(1), 19-27.

Fryar, Cheryl D., Yechiam Ostchega, Craig M. Hales, Guangyu Zhang, and Deanna Kruszon-Moran. "Hypertension prevalence and control among adults: United States, 2015-2016." (2017).

Gamper-Rabindran, Shanti, and Christopher Timmins (2011). "Hazardous Waste Cleanup, Neighborhood Gentrification, and Environmental Justice: Evidence from Restricted Access Census Block Data." *American Economic Review*, 101 (3): 620-24

Gershon, Andrea S., Chengning Wang, Jun Guan, Jovanka Vasilevska-Ristovska, Lisa Cicutto, and Teresa To. "Identifying patients with physician-diagnosed asthma in health administrative databases." *Canadian respiratory journal* 16, no. 6 (2009): 183-188.

Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, 1(1), 27–48. Glencross, D. A., Ho, T. R., Camina, N., Hawrylowicz, C. M., & Pfeffer, P. E. (2020). Air pollution and its effects on the immune system. *Free Radical Biology and Medicine*, 151, 56-68

Graff Zivin, J., & Neidell, M. (2013). Environment, health, and human capital. *Journal of economic literature*, 51(3), 689-730.

Graff Zivin, J., & Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7), 3652-3673.

Graff Zivin, J., Neidell, M., Sanders, N. J., & Singer, G. (2023). When externalities collide: Influenza and pollution. *American Economic Journal: Applied Economics*, 15(2), 320-351.

Grigorieva, E., & Lukyanets, A. (2021). Combined effect of hot weather and outdoor air pollution on respiratory health: Literature review. *Atmosphere*, 12(6), 790.

He, G., Pan, Y., & Tanaka, T. (2025). Air pollution and the airborne diseases: Evidence from China and Japan. *Journal of Environmental Economics and Management*, 130, 103104.

Hoffmann, B., & Rud, J. P. (2024). The unequal effects of pollution on labor supply. *Econometrica*, 92(4), 1063-1096.

Kerwin, JT, N Rostom, and O Sterck (2024). "Striking the Right Balance: Why Standard Balance Tests Over-Reject the Null, and How to Fix It." IZA DP 17217.

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2016). Caution, drivers! Children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, 98(2), 350-366.

Lee, David S., Justin McCrary, Marcelo J. Moreira, and Jack Porter. 2022. "Valid t-Ratio Inference for IV." *American Economic Review* 112 (10): 3260–90.

Lleras-Muney, A. (2010). The needs of the Army: using compulsory relocation in the military to estimate the effect of air pollutants on children's health. *Journal of Human Resources*, 45(3), 549-590.

Lleras-Muney, A., Schwandt, H., & Wherry, L. (2024). Poverty and Health. NBER WP.

Lyle, D. S. (2006). Using military deployments and job assignments to estimate the effect of parental absences and household relocations on children's academic achievement. *Journal of Labor Economics*, 24(2), 319-350.

Møller, P., Danielsen, P. H., Karottki, D. G., Jantzen, K., Roursgaard, M., Klingberg, H., ... & Loft, S. (2014). Oxidative stress and inflammation generated DNA damage by exposure to air pollution particles. *Mutation research/Reviews in mutation research*, 762, 133-166.

Moretti, E., & Neidell, M. (2011). Pollution, health, and avoidance behavior: evidence from the ports of Los Angeles. *Journal of human Resources*, 46(1), 154-175.

Neidell, M. J. (2004). Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *Journal of health economics*, 23(6), 1209-1236.

Neidell, M. (2009). Information, avoidance behavior, and health: the effect of ozone on asthma hospitalizations. *Journal of Human resources*, 44(2), 450-478.

Pint, E. M., Narayanan, A., Muggy, L., Kushner, J., Lachman, B. E., & Charan, S. M. (2024). *How Do Alternative Strategies for Army Installation Unaccompanied Housing Compare?*. RAND.

Pope Iii, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., & Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Jama*, 287(9), 1132-1141.

Pope, C. A., & Dockery, D. W. (2006). "Health effects of fine particulate air pollution: Lines that connect." *Journal of the Air & Waste Management Association*, 56, 709-741.

Robinson CH, Hussain J, Jeyakumar N, Smith G, Birken CS, Dart A, Dionne J, Garg A, Kandasamy S, Karam S, Marjerrison S, South AM, Thabane L, Wahi G, Zappitelli M, Chanchlani R. Long-Term Cardiovascular Outcomes in Children and Adolescents With Hypertension. *JAMA Pediatr*. 2024 Jul 1;178(7):688-698.

Richmond-Bryant, J., & Long, T. C. (2020). Influence of exposure measurement errors on results from epidemiologic studies of different designs. *Journal of Exposure Science & Environmental Epidemiology*, 30(3), 420-429.

Rietz, H., Pennlert, J., Nordström, P., & Brunström, M. (2023). Blood pressure level in late adolescence and risk for cardiovascular events: a cohort study. *Annals of Internal Medicine*, 176(10), 1289-1298.

Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management*, 98, 102250.

Schlenker, W., & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *The Review of economic studies*, 83(2), 768-809.

Sillman, Sanford, and Perry J. Samson. "Impact of temperature on oxidant photochemistry in urban, polluted rural and remote environments." *Journal of Geophysical Research: Atmospheres* 100.D6 (1995): 11497-11508.

Tran, H. M., Tsai, F. J., Lee, Y. L., Chang, J. H., Chang, L. T., Chang, T. Y., ... & Chuang, H. C. (2023). The impact of air pollution on respiratory diseases in an era of climate change: A review of the current evidence. *Science of the Total Environment*, 898, 166340.

Van Donkelaar, A., Hammer, M. S., Bindle, L., Brauer, M., Brook, J. R., Garay, M. J., ... & Martin, R. V. (2021). Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology*, 55(22), 15287-15300.

Zhang, Bin, Zhi-Fei Li, Zhuo-Yu An, Li Zhang, Jing-Yi Wang, Meng-Di Hao, Yi-Jing Jin et al. "Association between asthma and all-cause mortality and cardiovascular disease morbidity and mortality: a meta-analysis of cohort studies." *Frontiers in cardiovascular medicine* 9 (2022): 861798.

Appendix

Table A1. Association Between Prior-Year PM_{2.5} and Service Length

	Prior-year PM _{2.5}
Service length (ref: 5 years)	
6 years	0.031 0.039
7 years	-0.015 0.025
8 years	0.019 0.039
9 years	-0.009 0.045
10 years	0.068 0.043
≥ 11 years	0.063 0.036
F-statistic	1.63
Pr(F ≤ f)	0.16

Notes: The table reports coefficients from a regression of prior-year PM_{2.5} exposure on indicators for length of service. Soldiers with 5 years of service constitute the omitted reference category. Each coefficient represents the adjusted difference in prior-year exposure relative to soldiers who served for 5 years. The model includes primary military occupational specialty × skill qualification identifier × pay grade × assignment-quarter fixed effects. Standard errors, clustered at the duty-station level, are reported in parentheses. The F-statistic and p-value test the joint null hypothesis that all service-length coefficients equal zero.

Table A2. Sensitivity of OLS Estimates to Alternative Control Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Circulatory condition						
OLS	8.42 (0.98)	-1.74 (1.13)	-2.18 (1.03)	-1.65 (0.92)	-1.98 (0.90)	-1.36 (0.82)
OLS, climate controls	10.92 (1.54)	-2.51 (1.53)	-2.44 (1.33)	-2.17 (1.28)	-2.35 (1.17)	-1.77 (1.27)
Panel B: Respiratory condition						
OLS	2.51 (1.91)	0.59 (2.36)	-0.49 (2.11)	-1.48 (1.78)	-1.85 (1.74)	-1.08 (1.80)
OLS, climate controls	1.60 (2.67)	-1.74 (3.49)	-1.49 (3.28)	-3.41 (2.67)	-3.16 (2.66)	-3.00 (2.71)
<i>Controls</i>						
Quarter-year		✓	✓	✓	✓	
Individual characteristics			✓		✓	
PMOS × SQI × pay grade				✓	✓	
PMOS × SQI × pay grade × quarter						✓

Notes: The table reports ordinary least squares (OLS) estimates of the relationship between average PM2.5 exposure and circulatory and respiratory conditions. Each outcome is measured as the number of soldiers per 1,000 with at least three diagnoses during the study period. Coefficients represent the change in the outcome rate per 1,000 soldiers associated with a 1- $\mu\text{g}/\text{m}^3$ increase in average exposure. Column (1) includes no assignment or individual controls. Columns (2)-(5) include different combinations of assignment-quarter indicators, individual characteristics, and primary military occupational specialty × skill qualification identifier × pay-grade fixed effects. Column (6) includes primary military occupational specialty × skill qualification identifier × pay grade × assignment-quarter fixed effects. Specifications labeled “OLS with climate controls” additionally adjust for climate variables. Standard errors, clustered at the duty-station level, are reported in parentheses.

Table A3. Characteristics of the Sample and Estimated Compliers

	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 mean characteristics of the full analytic sample with estimated mean characteristics of compliers. Complier characteristics are estimated using the κ -weighting method developed by Abadie (2003). Compliers are soldiers whose average PM2.5 exposure is affected by the instrument, prior-year exposure.