Effects of Early-Childhood Exposure to Ambient Lead and Particulate Matter on Adult Personality

Arthur Fraas, Randall Lutter, Joshua Murphy, Qinrui Xiahou, Jeff Potter, and Samuel D. Gosling

Working Paper 23-17
May 2023

About the Authors

Arthur Fraas is a visiting fellow at RFF. Fraas works on a variety of issues related to energy and the environment, including projects looking at the development of retrospective analyses of major environmental rules, the potential regulation of greenhouse gases under the Clean Air Act, and issues and tradeoffs with energy efficiency regulations. He retired in 2008 from OMB after serving 21 years as chief of the Natural Resources, Energy, and Agriculture Branch in OIRA. Before joining the OMB, Fraas was a senior economist at the Council on Wage and Price Stability, a staff member of the Senate Judiciary Subcommittee on Antitrust and Monopoly, an assistant professor of economics at the US Naval Academy, and a staff economist with the Federal Reserve System.

Randall Lutter, PhD, is a senior fellow at the Manhattan Institute, where his research focuses on pharmaceutical markets and policy, medical innovation, and regulation. As senior science and regulatory advisor in the Office of the Commissioner at the U.S. Food and Drug Administration (FDA) from 2017 to 2020, Dr. Lutter led projects involving competition in pharmaceutical markets and drug pricing, the regulation of tobacco products, and surveillance of medical product supply chains disrupted by Covid-19. His work draws from more than 25 years of senior experience in the analysis and management of federal programs to protect health, safety, and the environment.

Joshua Murphy is a senior economist at Natural Resources Canada. He obtained a Ph.D. in economics from the University of Toronto. His thesis examined the costs, benefits, and efficiency of air quality regulation, including the Clean Air Act of 1970 and the Clean Air Interstate Rule.

Qinrui Xiahou is a PhD student in Economics at the University of Hong Kong. Prior to joining HKU, she was a Research Analyst at Resources for the Future, a Student Research Fellow at the Yale Hixon Center for Urban Ecology, and a Student Associate of the Yale Climate Change and Health Initiative. Qinrui's research focuses on climate change economics and policy. Her work involves employing econometrics and energy modeling methods to analyze a wide array of policies, such as the Solarize Campaign in the state of Connecticut, the low-carbon transition pathways in China, the Clean Energy for America Act in the United States, and the Cap-and-Trade Program in California. She graduated from Yale University in May 2021 with a master's degree in Environmental Science.

Jeff Potter is chief technology officer of Enveritas, a Y Combinator-backed non-profit working to improve the livelihoods of coffee farmers around the world. Previously, he was the vice president of engineering at the James Beard-winning website Food52.

One of his earliest projects was a site about personality, **The Big Five Project**. It's still popular; over 15 million people have learned about themselves from the site.

Samuel D. Gosling is a professor at the University of Texas at Austin. He has three main areas of interest: Connections between people and the physical spaces in which they live, personality in nonhuman animals, and new methods for obtaining data useful for research in the social sciences.

Acknowledgments

The authors gratefully acknowledge help from Ted Schwaba, who graciously answered questions about his data and code. We also acknowledge assistance from David Evans, Carl Pasurka, and Chris Clotworthy who helped assemble data for our lead density calculations. Reed Walker and Adam Isen provided their data files (with the exception of confidential Census data). Fraas and Xiahou acknowledge financial support from the Smith Richardson Foundation.

About RFF

Sharing Our Work

Abstract

To assess how early-life exposure to air pollution affects adult personality, we use new annual lead (Pb) vehicle emissions data by county, for 1969 to 1981, and "Big Five" personality data for 130,000 adults. Models with county and cohort fixed effects show higher Pb exposure during the first five years of life lowers agreeableness and increases openness. Weaker evidence suggests Pb lowers conscientiousness and increases neuroticism but it has no effect on extraversion. We also assess how regulation-induced cuts in total suspended particulates (TSP) levels affect adult personality. We are unable to disentangle early life effects of Pb and TSP.

Contents

1. Introduction

The environmental economics literature has typically focused on a familiar set of outcomes related to mortality, morbidity, and environmental quality, and sometimes cognitive performance, but not noncognitive personality traits. Effects on personality, however, may also be important, especially for family relationships and labor market performance. Identifying the causal effects on personality of early-life environments has been difficult because these environments are so multidimensional and relevant quasi-experiments are rare. Schwaba et al. (2021) provide the first analysis we are aware of about effects of early-life exposure to air pollution on subclinical adult personality traits.

We contribute to the literature on effects of early-life exposure to pollutants on adult outcomes in three different ways. First, we develop and analyze novel county-level annual data on vehicular lead (Pb) emissions, using the volume of gasoline sold, its lead content, and other data. Second, we improve modeling of the effects of lead on personality by introducing fixed effects for counties and cohorts and exploring different periods of exposure during early childhood. Finally, we seek to disentangle the effects of two airborne pollutants (Pb and particles) on adult personality.

Following Schwaba et al. (2021), we use "Big Five" personality traits from more than 132,000 respondents to an Internet survey. These traits (agreeableness, conscientiousness, extraversion, neuroticism, openness) are derived from statistical analyses and may be identifiable through close observation by a stranger (McAdams 1995), as they are readily observable. Cobb-Clark (2012) report that these traits are stable in adulthood, and Cubel et al. (2016) and Donato et al. (2017) find that they predict labor productivity.

We develop new measures of annual lead emissions from motor vehicles by county because leaded gasoline was the primary source of lead in residential environments (e.g., EPA Office of Policy Analysis 1985). Our approach relies on publicly available data to provide measures of annual Pb density at the county level and at the urban core within counties. We also identify difficulties inferring county-level air quality measures from the Pb monitoring data available to Schwaba et al. (2021). Given that limited data, decisions about the location of new monitors, and the relocation of existing ones, as well as their upkeep and maintenance, simply aggregating monitoring data—with the necessary interpolation and extrapolation to address missing data—compromises efforts to provide a measure of annual county-level air quality. We compare the new vehicular lead emissions data with the Schwaba et al. (2021) Pb monitoring data.

We examine the effects of reduced lead exposure using Schwaba et al.'s (2021) sample of counties (269) and modified versions of their regression specifications. We assess the relative effectiveness of lead exposure measures—including Schwaba et al.'s (2021) measures of ambient lead based on monitoring data and our new measure based on motor vehicle emissions—in explaining variations in adult personality traits. Following Schwaba et al. (2021) and Reyes (2007, 2015), we focus on changes in lead emissions and exposure associated with EPA actions under the Clean Air Act (CAA) to reduce lead in gasoline. The regulations introduced during the 1970s caused variations in lead levels that were not closely tied to local conditions and, therefore, plausibly exogenous. The timing of reductions in lead levels during that decade was driven by refineries' choices, considering both EPA's requirements for the lead content of their gasoline and their broader regional marketing opportunities (volumes and blends of gasoline sold within regional marketing districts). We isolate the effects of early-childhood exposure to high-density vehicular lead emissions on adult personality through several refinements. We introduce county-level fixed effects and cohort fixed effects and use standard errors clustered by county. We also examine how effects of childhood exposure vary with different periods of exposure (e.g., birth year, first five years).

Finally, we assess effects of regulation-induced reductions in total suspended particulates (TSP) during the 1970s on adult personality traits. This analysis applies some of the methods employed by Isen et al. (2017) and related papers (Chay and Greenstone (2003), Chay et al (2003), Chay and Greenstone (2005)), that use the designation of nonattainment areas in 1972 (implementing the CAA requirements for attaining the National Ambient Air Quality Standards (NAAQS)) as a quasi-experiment (i.e., two-stage least-squares estimates based on before-after 1972, attainment–nonattainment comparisons). We applied this approach to a set of counties broader than the 148 in Isen et al. (2017). We avoid potential bias derived from TSP monitor placement by using a set of monitors in locations that are unchanged during our analysis period.

The rest of the paper is organized as follows. Sections 2 and 3 provide background information on the literature and regulatory requirements. Sections 4 and 5 present our preregistered hypotheses and our identification strategy. Section 6 presents our data. Our results and conclusions end the paper. The appendices offer details.

2. Literature

Two quite different papers report that exposure to air pollution during infancy and early childhood adversely affects adult outcomes. First, using the 1970 CAA as a quasi-experiment, Isen et al. (2017) show that regulation-induced reductions in early-life exposure to TSP increases adult employment and earnings. Their analysis uses administrative data from the US Census Bureau's Longitudinal Employer Household Dynamics file, which includes information on labor market outcomes at age 30 and county of birth for millions of individuals in 24 states.

Schwaba et al. (2021), interpreting ambient concentrations of lead as exogenous, reported effects of early-life exposure to airborne lead on normal-range personality traits. They report that US adults growing up "in counties with higher level atmospheric lead levels had less adaptive personality profiles, were less agreeable and conscientious and, among younger participants, more neurotic." Schwaba et al. (2021) argue that these effects are important because they can affect well-being and lifetime earnings. This association was statistically significant for adults in their twenties and thirties but not older. The authors use the observed peak year of average ambient lead concentrations in a county to date the beginning of lead in gas emissions control efforts. They do not address whether some peaks may reflect random variation in monitoring methods or market conditions, as opposed to the beginning of emissions controls, although they note that other changes in the 1970s may also have contributed to these changes.

The two studies, by focusing on distinct but interrelated impacts of different air pollutants, invite an integrated assessment of how air pollution during early life can affect adult outcomes. We take steps toward such an assessment.

A broader literature also considers the effect of early-childhood Pb exposure on cognitive effects (such as IQ) and behavior in later childhood. For example, Reyes (2007, 2015) reports effects of early-childhood exposure on behavior, including teenage aggressive behavior and criminal behavior. Other literature reporting behavioral effects of childhood Pb exposure in the United States on crime include Nevin (2000), and Masters et al. (1998).

In federal regulatory analyses, the cognitive effects of lead have been more important than its noncognitive effects. In its most recent regulatory impact assessment of reducing children's exposure to lead, EPA (2020, ES–15) noted that "to estimate the [quantifiable] benefits of the regulatory options for each affected child, the estimated value of an IQ point based on its effect on lifetime earnings is multiplied by the estimated change in avoided IQ decrement." EPA (2020) added that "some studies found that noncognitive personality traits are at least as predictive of life outcomes as IQ," citing Borghans et al. (2016) and Heckman et al. (2006).

EPA's (2020) analysis, however, only discusses the qualitative effects on outcomes other than IQ, noting that some (e.g., attention deficit/hyperactivity disorder and noncognitive skills, such as effort and initiative) adversely affect labor earnings. Some assessments of the impact of cognitive performance on labor market outcomes have taken into account noncognitive skills (e.g., Lin et al. (2018)), but limitations on measuring these skills have hindered such assessments.

Other adverse effects of lead include shortened attention span and increased risk for antisocial and criminal behaviors, according to Landrigan et al. (2018) and EPA (2013). In a study on the phaseout of lead in gasoline in Sweden, Nilsson (2009) reports a nonlinear relationship between local air lead levels in early childhood and labor market outcomes for young adults, with an adverse effect that is greater for children of lower socioeconomic status. Reyes (2007, 2015) finds large negative consequences of early-childhood lead exposure, in the form of an unfolding series of adverse behavioral outcomes culminating in criminal behavior for some young adults.

3. Regulatory Requirements

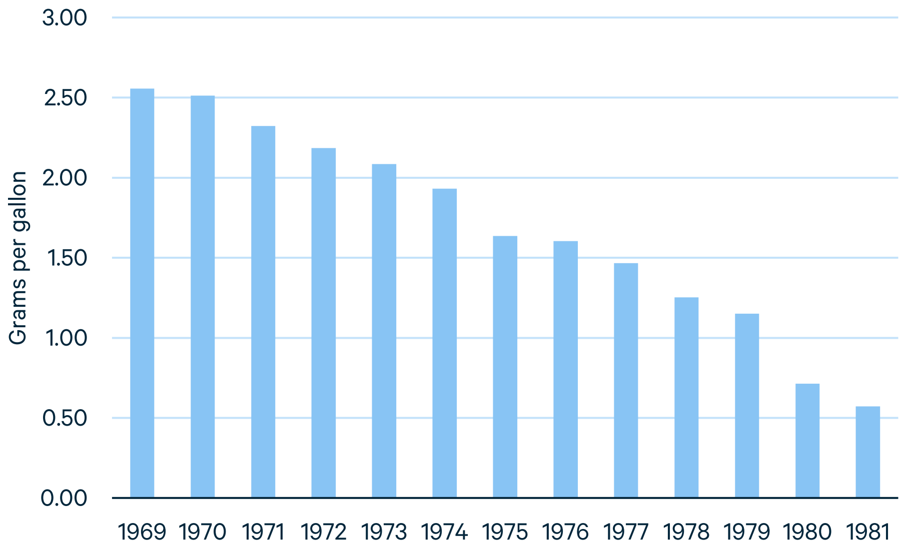
Obtaining good estimates of the effects of TSP and lead regulations during the 1970s requires a nuanced understanding of the implementation of the CAA of 1970, which directed EPA to set national air quality standards for six major air pollutants (including TSP) and provided the legal framework for regulating lead in gasoline.

Pb. Lead is a neurotoxin with demonstrated adverse effects of childhood exposure on the developing nervous system. In early 1971, the EPA administrator declared that "an extensive body of information exists which indicates that the addition of alkyl lead to gasoline [...] results in lead particles that pose a threat to public health." In early 1972, EPA proposed a rule requiring refiners to produce a nonleaded grade of gasoline and a schedule for the phasedown of lead in gasoline. In 1973, EPA issued final rules requiring the production of a nonleaded gasoline (37 *Federal Register* (FR) 10842) and a schedule for the phasedown to a 0.6 g/gallon. The rule faced legal challenges, delaying its implementation, but was upheld in early 1976 by the DC Circuit court. Until then, no binding federal restrictions addressed lead content in gasoline, though refiners were required to provide unleaded along with leaded fuels, and by 1975, unleaded gasoline had become widely available. In the last part of the 1970s, the EPA's refinery-specific caps on lead content gave refiners flexibility in determining the lead content of gasoline delivered to various local markets, though the caps were also stringent enough to drive significant reductions in the average lead content across all marketing districts and states.

Figure 1 shows that the average amount of lead in gasoline sold fell from 2.56 grams per gallon in 1969 to 0.57 grams per gallon in 1981, with the largest year-to-year decline in 1980.[1]

[1] The Data section describes data. For a given state, the average lead content of gasoline is defined as the sales volume (in gallons) weighted average of the lead content of individual fuels (regular, premium, unleaded). The national average lead content was obtained by taking sales volume weighted averages of the state averages.

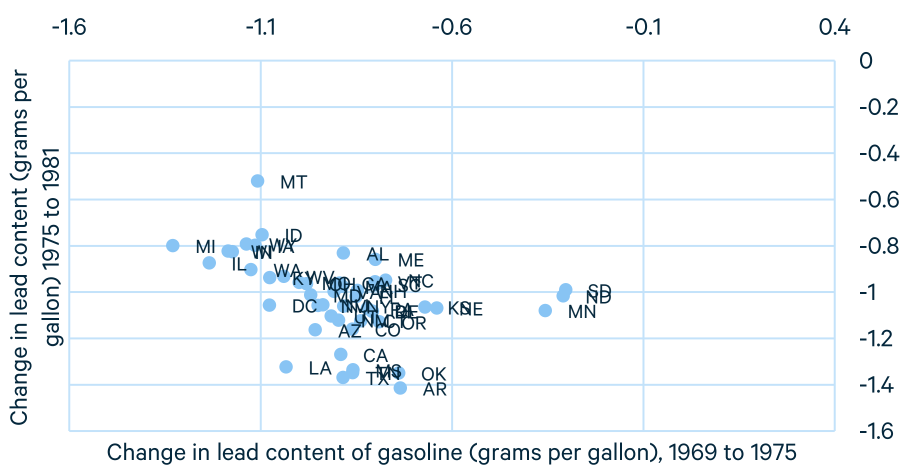
Figure 1. Trend in the Average Lead Content of Gasoline Sold in the US



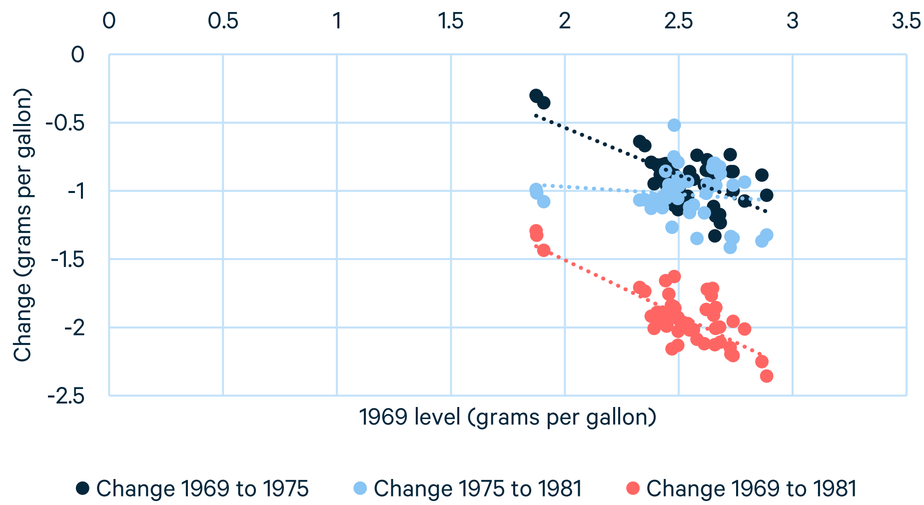
Although the lead content of gasoline declined in all states in both the early and late 1970s, the phasedown varied in extent and timing. The earliest and strongest declines were in Michigan, Indiana, Illinois, Iowa, and Wisconsin. States that initially saw relatively weak declines in the early 1970s, such as Oklahoma, Arkansas, Missouri, Texas, and Kansas, caught up via relatively strong declines later in the decade (Figure 2a shows a negative correlation between changes in lead content in the early versus late 1970s). Because the regulations ultimately required refiners everywhere to meet the same standard, those states with the highest initial lead content (e.g., Texas, Louisiana) saw the largest declines during the entire decade (Figure 2b).

Figure 2. Differences in The Timing of The Lead Phasedown across States during the 1970s

Panel A: Early versus Late Reductions in The Lead Content of Gasoline



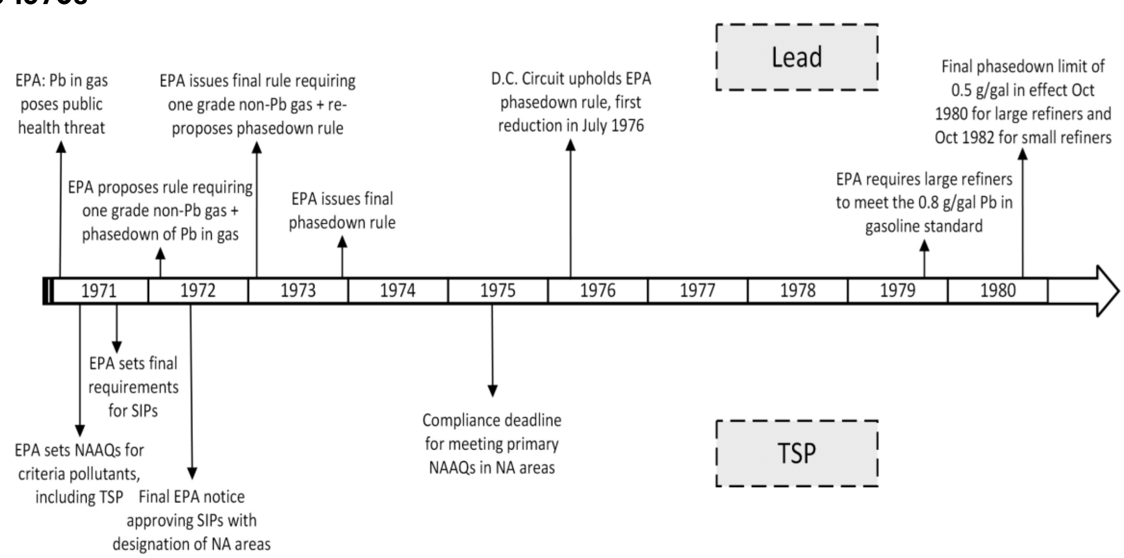
Panel B: Changes in The Lead Content of Gasoline versus Initial Levels



TSP. The CAA required EPA to set NAAQS in early 1971 for six criteria air pollutants, including TSP (36 *FR* 8186). To bring areas into attainment with the NAAQS, the 1970 CAA established a formal process requiring states to submit specific implementation plans for EPA approval. These plans had to identify nonattainment areas and adopt the control measures necessary to meet and maintain the NAAQS (37 *FR* 10842). In its 1972 final rule approving the state plans, EPA recognized that "the aggregate emission control requirements of the 55 State plans will create such a great demand for clean fuels, emission control equipment, and other items that attainment of the primary standards in many urban areas in significantly less time than 3 years generally will not be feasible" (37 *FR* 10843).

Figure 3 summarizes steps taken by EPA in the 1970s to regulate Pb emissions from motor vehicles and implement the NAAQS for TSP.

Figure 3. Key Steps in Federal Regulation of Lead and Total Suspended Particulates Emissions in the 1970s



4. Hypotheses

We present our four preregistered hypotheses—noting that additional hypotheses were developed during preliminary data analysis.

First, as Pb from motor vehicle emissions is considered the primary source of exposure in residential environments, we hypothesized that our new measure of county-level annual density of vehicular Pb emissions is positively correlated with ambient monitoring data.

Second, we expected our measure to better explain variations in adult personality traits in the Schwaba et al. (2021) framework, as it may better reflect population exposure.

Third, we hypothesized that Pb exposure through the first five years of life (including in utero for children born late in the calendar year) will predict adult personality roughly as well as measures of exposure over 18 years of childhood. While Schwaba et al. (2021) report associations between cumulative Pb exposure over the first 18 years and adult personality traits, multiple authorities suggest the key period is the first six years. The CDC's blood Pb reference level, for example, is based on data from children ages 1–5 (Ruckart et al (2021). Its Lead Poisoning Prevention Program states "Children less than six years old are at a higher risk of lead exposure [...] because their bodies are rapidly developing and more susceptible to taking in lead if exposed" (CDC undated). The US Department of Health and Human Services' goal to reduce childhood exposure to Pb focused on children under six years old (Ruckart et al (2021).

Fourth, using the nonattainment provisions of the CAA of 1970 to isolate exogenous reductions in TSP similar to Isen et al. (2017), we expected to find that exposure to TSP while in utero and up to age 6 will have an additional effect (after controlling for Pb exposure) personality traits. In implementation, we shifted our focus to exposure limited to the year of birth, for simplicity and consistency with Isen et al. (2017).

5. Identification

We apply the identification strategy of Schwaba et al. (2021), who use the phasedown of Pb in gasoline to identify exogenous reductions in Pb pollution. We also use the same model specification, except we introduce county fixed effects, cohort fixed effects, clustering of standard errors by county, and a new measure of Pb that avoids reliance on interpolations and extrapolations to resolve sparse and intermittent ambient monitoring from before the phaseout of leaded gasoline. Our introduction of county fixed effects means that we exploit variation in the timing and extent of Pb reductions across counties.

We also apply the identification strategy of Isen et al. (2017), who use the introduction of NAAQS for TSP to estimate causal effects of reductions in TSP pollution. Following Isen et al. (2017), we identify effects of TSP by using an indicator variable for whether a given county's air quality in 1971 met or exceeded the standard for TSP that EPA issued in 1971.

6. Data

The data in our analysis are available from government sources, appear in studies, including supplemental material from Schwaba et al. (2021) and Isen et al. (2017), or come from historical (paper) documents available in research libraries. We use EPA monitoring data for airborne concentrations of Pb and TSP, GPIPP data on personality traits measured on a scale of 1–5, family characteristics, and county-level economic, environmental, and demographic variables.

We construct a new measure of the density of Pb emissions from motor vehicles by county and calendar year using data from several sources:

- Quantity sold in gallons, by month and grade, of leaded and unleaded fuel, by state and for DC, 1970–1982. Ethyl Corporation (Petroleum Chemicals Division) provides these data in its Yearly Report of Gasoline Sales: By States.

- Pb content of gasoline (grams per gallon) by grade (premium, regular, unleaded), for each of 17 marketing districts, which together cover the United States, by season (summer = June, July, and August; winter = December, January, and February), for 1968–1982. The source is DOE Bartlesville Energy Research Center.

- EPA's data on nitrogen oxides (NO_x) emissions from motor vehicles by state and by Air Quality Control Regions covering all counties in all states, 1972–1980, from the annual National Emissions Report (of EPA's National Emissions Data System), beginning in 1972. We use NO_x emissions to apportion state-wide gasoline use to AQCRs.

- Census data on population by county and state, by year. Estimates of county populations by calendar year since 1969 are available at **https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-detail.html**. We use AQCR population to estimate per capita Pb emissions from motor vehicles within an AQCR.

- We use census data to estimate population density in the core urban area within the county. **https://www2.census.gov/prod2/decennial/documents/1980/1980**

censusofpopu8011uns_bw.pdf (for the 1980s) and **https://www.census.gov/library/publications/1973/dec/population-volume-1.html#par_textimage_43** (for the 1970s).

More specifically, our calculation sums across all leaded grades of gasoline the product of the Pb content (grams/gallon) and the gallons sold. We calculate vehicular Pb emissions for each AQCR by multiplying estimates of Pb emissions for a specific state and a specific year by that AQCR's vehicular NO_x divided by state-wide vehicular NO_x emissions in that same year.

Some counties, such as Alameda County CA, have areas with low population densities and other areas that are quite urban and densely populated. Since these patterns of development may lead to Pb emissions that are heterogeneous within a county, we construct a measure of Pb density for the urban core, which implies that exposure outside the urban core is negligible. In counties with no urban core, we use an estimate of countywide Pb density—countywide Pb emissions divided by countywide geographic size.

Our measure of Pb emissions from motor vehicles in core urban areas is predictive of monitored ambient Pb concentrations. Table 1 reports cross-sectional correlations between our measures of Pb density and the county average of monitor-specific annual mean Pb concentrations in 1975, partway through the phasedown. Excluding source-oriented monitors from the calculation of county-average Pb concentrations, or dropping counties with primary Pb or copper smelters altogether, improves the correlations considerably, as our measure of Pb density focuses solely on traffic-related pollution, whereas ambient monitoring is also affected by large industrial emitters. Other adjustments, such as excluding monitors that are high above ground (which may not be affected by vehicle emissions) or have fewer than five readings (an EPA requirement for valid quarterly data), have negligible effects on the correlations. The log-log formulation provides the best fit. Our measure of Pb density that focuses on the urban core significantly outperforms county-average Pb density, consistent with requirements for state and local authorities to focus monitoring efforts on the most heavily urbanized areas. These correlations demonstrate the predictive ability of our measure.

Table 1. Correlations between Lead Density and Monitored Ambient Lead Concentrations

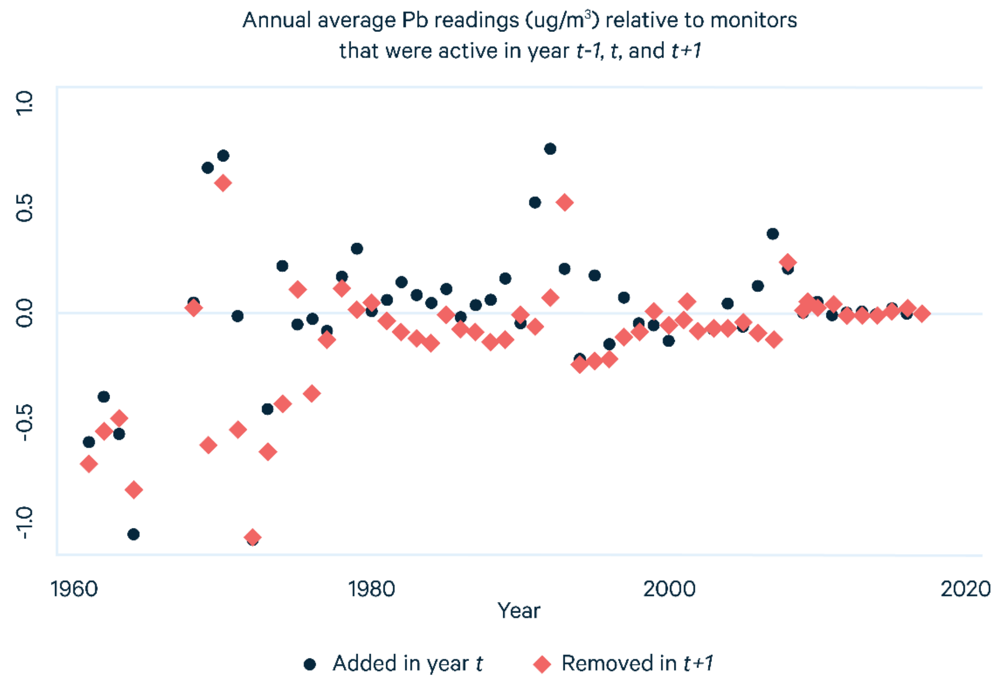
			Excluding source-oriented monitors			
	All counties and monitors	Excluding counties with smelters	All counties and monitors	Excluding monitors >15 feet above ground	Excluding monitors with <5 readings per year	Log-log, all counties and monitors
Lead density measure (kg per sq. mile)	(1)	(2)	(3)	(4)	(5)	(6)
Unadjusted	0.19	0.26	0.26	0.26	0.29	0.26
Urban adjusted	0.27	0.40	0.40	0.42	0.41	0.75
# Counties	235	224	231	171	221	231

Note: Each county's ambient lead concentration is the simple average of monitor-specific annual means. Only 235 counties had valid lead monitoring data in 1975.

The ambient Pb and TSP monitoring data used for the analysis are from the EPA's Air Quality System. Ambient Pb concentrations were themselves based on analysis of TSP filters. While TSP monitors and monitored counties increased quickly during the early and mid-1970s due to CAA monitoring requirements (Murphy 2017), the number of monitors reporting ambient Pb concentrations were—with the exception of more intensive monitoring efforts in 1968 and 1975—generally quite limited until the late 1970s. Sampling was infrequent, with most monitors recording 30 to 60 24-hour averaged (daily) readings per year.

Pb monitoring was somewhat more haphazard than TSP monitoring, with less frequent sampling throughout the year and more churning from one year to the next (a location being monitored in one year and not monitored in the next). In addition to the lack of continuous and long-term Pb monitoring data, measuring trends in Pb concentrations is further complicated by an apparent effort to manage the monitor network so as to detect high Pb concentrations yet minimize the overall cost of monitoring. As shown in Figure 4, using annually averaged data, we found a consistent effort to conduct new sampling (or restart sampling) in areas with relatively high Pb concentrations and to cease sampling in areas with relatively low concentrations. For these reasons, we suggest caution when interpreting results based on trends in ambient Pb concentrations (we use Schwaba et al.'s (2021) county-year panel in some regressions) and prefer instead those based on our measure of vehicular Pb emissions.

Figure 4. Differences in Ambient Lead Concentrations among Remaining, New, and Retiring Monitors



Note: For a given year, *t*, the dark blue dots represent differences in the annual average of 24-hour readings in that year between "remaining monitors" (those active in years *t*-1, *t*, and *t*+1) and "new monitors" (monitors active in year *t* but not year *t*-1), and the coral dots represent differences between remaining monitors and "retiring monitors" (monitors active in year *t* but not year *t*+1).

Our analysis covers 250 counties included in Schwaba et al. (2021) (excluding Alaska, Hawaii, and Puerto Rico). We use the GPIPP personality traits data at the individual level. The GPIPP website has collected personality data for millions of people since the early 2000s (Schwaba et al. 2021). Schwaba et al. (2021) provided access to 59 years (1960–2018) of Pb monitoring data for the 269 counties in their analysis, including interpolations and extrapolations. Consistent with Isen et al. (2017), we have access to 9 years (1969–1977) of data for annual TSP measures (though not necessarily for all 269 counties). Table A3.1 in Appendix 3 presents summary statistics of the variables used in our statistical analyses.

7. Results

Using the data and code provided by Schwaba et al. (2021), we replicate their published results and then modify their analysis in several ways. We control for fixed effects for counties and five-year cohorts (beginning in 1965, 1970, etc.), so that our measure of the effect of Pb concentrations reflects variations within a county and within a cohort. We also use standard errors clustered by county. We transform the ambient Pb concentrations by using natural logs and find that the effect of (the log of) ambient Pb concentrations is statistically significant at the 95 percent confidence level, as shown in Table 2 for agreeableness. Using a period of exposure of five years beginning with the birth year improves the statistical significance level to 99 percent confidence and leaves the R^2 unchanged. Limiting the analysis to only those years for which we have Pb density data (birth years 1969–1977) increases the absolute value of the effect from 0.022 to 0.082, leaving it statistically significant at the 99 percent level and raising the R^2 from 0.14 to 0.18. Thus, we find evidence to support the first hypothesis that Pb exposure in the first five years predicts personality traits as well as exposure in the first 18 years does.

In Model 4, we present a measure of Pb density expressed as annual emissions per square meter of core urban areas in the county. We first consider a measure of vehicular Pb emissions constructed without adjustment for the urban core but discover that the adjustment performs better, as discussed in Appendix 2. We find that the adjusted measure predicts adult agreeableness as well as the ambient Pb measure used in Model 3—the coefficient for Pb density has a slightly higher t-ratio and the equations yield the same R^2. In online Appendix 4, Tables A4.1 to A4.5, we present similar tables for all five personality traits.

Table 2. Effects of Early-Life Exposure to Lead on Adult Agreeableness

	(1)	(2)	(3)	(4)
log(Lead concentration+1)	-0.032 (0.029)	-0.022* (0.013)	-0.082*** (0.026)	
log(Lead density (adj)+1)				-0.124*** (0.035)
Age	0.026*** (0.001)	0.026*** (0.001)	0.027*** (0.001)	0.027*** (0.001)
Parental college	-0.014*** (0.004)	-0.014*** (0.004)	-0.040*** (0.006)	-0.040*** (0.006)
Median county income	-0.161*** (0.005)	-0.161*** (0.005)	-0.247*** (0.009)	-0.247*** (0.009)
Period of Exposure	18 years	5 years	5 years	5 years
Cohort			1969–1977	1969–1977
Avglead	0.181	0.433	0.987	1.459
Sdlead	0.326	0.571	0.53	1.098
Observations	1,059,813	1,059,813	132,383	132,383
R^2	0.014	0.014	0.018	0.018
Adjusted R^2	0.014	0.014	0.016	0.016

Notes: All data except lead density are from Schwaba et al. (2021). Parentheses contain standard errors, clustered at the county level. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of nonzero monitor readings within the county over the first five years of life (µg /m3). The mean and standard deviation are displayed as “Avglead” and “Sdlead.”

As shown in Table 3, using the log of Pb concentrations, dummies for counties and cohorts, five-year periods of exposure, and standard errors clustered by county leads to statistically significant effects of the log of ambient Pb concentrations on agreeableness; the effects of extraversion and openness are statistically significant at the 95 and 90 percent levels, respectively. No statistically significant effect was found on conscientiousness and neuroticism.

Table 3. Effects of Ambient Lead Concentrations During Early Life on Adult Personality

	Agr (1)	Con (2)	Ext (3)	Neu (4)	Ope (5)
log(Lead concentration+1)	-0.082***	-0.036	0.056**	0.024	0.055*
	(0.026)	(0.033)	(0.028)	(0.030)	(0.029)
Age	0.027***	0.027***	0.008***	-0.025***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.040***	-0.078***	0.019***	-0.048***	0.248***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Median county income	-0.247***	-0.160***	-0.039***	0.210***	0.053***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.009)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avglead	0.987	0.987	0.987	0.987	0.987
Sdlead	0.538	0.538	0.538	0.538	0.538
Observations	132,383	132,383	132,383	132,383	132,383
R^2	0.018	0.091	0.006	0.018	0.027
Adjusted R^2	0.016	0.089	0.004	0.016	0.025

Note: Traits are agreeableness, conscientiousness, extraversion, neuroticism, and openness. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of nonzero monitor readings within the county over the first five years of life (µg /m3). The mean and standard deviation are displayed as "Avglead" and "Sdlead."

In Table 4, we use our measure of vehicular Pb emissions density in urban cores instead of ambient Pb concentrations. We believe our measure avoids sparse and incomplete monitoring of ambient concentrations before the mid-1970s and the resulting need for interpolations or extrapolations used by Schwaba et al. (2021). It also sidesteps biases that may be associated with strategic choice of ambient Pb monitoring locations.

Using our measure, we find that the t-ratios improve for agreeableness, conscientiousness, neuroticism, and openness but not extraversion. Effects of Pb density in early life are statistically significant at the 99 percent level for agreeableness and openness and at the 95 percent level for conscientiousness and neuroticism. The signs of the coefficients for all traits are the same in the models with Pb density as in the models with ambient Pb concentrations.

Comparing our results with the results that Schwaba et al. (2021) emphasize, we find that agreeableness and conscientiousness have a negative effect that is strongly statistically significant (at the 95 percent or greater level). In addition, we also find a positive effect that is strongly statistically significant for openness. Finally, although Schwabe et al. (2021) only report a positive effect for neuroticism with additional controls among younger respondents, we find a more robust positive effect that is statistically significant at the 95 percent level.

We also consider models using Pb instead of the log of Pb, although such models implicitly assign greater influence to declines in the few counties that have high initial levels. In these models, presented in online Appendix 4 in Table A4.6, ambient Pb concentration has a statistically significant negative effect on agreeableness (at the 99 percent level), a positive effect on extraversion (at the 95 percent level), and a positive effect on openness (at the 90 percent level). Replacing it with Pb density changes these results slightly (Table A4.7). Pb density has a statistically significant negative effect on agreeableness (at the 95 percent level), no effect on extraversion, and a positive effect on openness (at the 99 percent level). In models treating concentration and density linearly, no statistically significant effect appeared for conscientiousness and neuroticism.

We are not aware of a theoretical reason why the relationship between Pb exposure and each of the Big Five personality traits should be the same for all five traits and believe additional analysis of the functional form of such relationships may be warranted.

Before exploring potential effects of early-life exposure to TSP and personality, we consider whether the results vary if we limit our analysis to only those counties for which we have valid ambient TSP data from 1969 to 1981 from a set of monitoring locations that generated TSP data for all the years in our analysis period. Imposing this constraint does not change any of the results in Tables 3 and 4.

Table 4. Effects of Vehicular Lead Emissions during Early Life on Adult Personality Traits

	Agreeableness	Conscientiousness	Extraversion	Neurotic	Openness
	(1)	(2)	(3)	(4)	(5)
log(Lead density+1)	-0.124***	-0.066**	0.021	0.068**	0.183***
	(0.035)	(0.030)	(0.034)	(0.032)	(0.039)
Age	0.027***	0.027***	0.008***	-0.025***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.040***	-0.078***	0.020***	-0.048***	0.248***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Median county income	-0.222***	-0.147***	-0.041***	0.195***	0.012
	(0.014)	(0.013)	(0.012)	(0.014)	(0.012)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avglead	1.459	1.459	1.459	1.459	1.459
Sdlead	1.098	1.098	1.098	1.098	1.098
Observations	132,383	132,383	132,383	132,383	132,383
R^2	0.018	0.091	0.006	0.018	0.028
Adjusted R^2	0.016	0.089	0.004	0.016	0.026
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977

Note: Dependent variables are agreeableness, conscientiousness, extraversion, neuroticism, and openness. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead density is the average estimated lead emissions divided by area within the county over the first five years of life (µg /m2). The mean and standard deviation are displayed as “Avglead” and “Sdlead.”

In Table 5, we present results of the basic model of personality traits using the predicted values of TSP based on an instrumental variable approach developed by Isen et al. (2017), which uses a county’s status regarding nonattainment of the initial NAAQS for TSP. In this model, we avoid complications from the strategic behavior of local air quality regulatory agencies by including TSP data from only those locations that have monitors active in every year from 1969 through 1977.

Exposure to TSP in the birth year has statistically significant negative effects on agreeableness and conscientiousness and a positive effect on openness (all at the 99 percent confidence level). Effects on extraversion and neuroticism are not significant. For all five traits, the data reject the null hypothesis that the instrument is weak at conventional levels of significance and the hypothesis that the independent variable (IV) estimate is equivalent in consistency to simple OLS estimates, except for extraversion.

Table 5. Effects of Exposure to TSP in The Year of Birth on Adult Personality Traits Using Instrumental Variables

	Agreeableness	Conscientiousness	Extraversion	Neurotic	Openness
	(1)	(2)	(3)	(4)	(5)
TSP	-0.003***	-0.003***	-0.0003	0.002	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.028***	0.028***	0.008***	-0.026***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.042***	-0.080***	0.020***	-0.046***	0.242***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)
Median county income	-0.169***	-0.122***	-0.083***	0.202***	0.003
	(0.027)	(0.026)	(0.023)	(0.032)	(0.032)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avgtsp	88.354	88.354	88.354	88.354	88.354
Sdtsp	27.61	27.61	27.61	27.61	27.61
Weak instruments	0.000	0.000	0.000	0.000	0.000
Wu-Hausman	0.001	0.001	0.959	0.049	0.000
Observations	97,440	97,440	97,440	97,440	97,440
R^2	0.017	0.090	0.005	0.018	0.025
Adjusted R^2	0.015	0.088	0.003	0.016	0.023

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level and presented in parentheses. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. TSP emissions are at the county level in the birth year. The mean and standard deviation are displayed as "Avgtsp" and "Sdtsp." The *p*-values of the regression diagnostics are presented in the "Weak instruments" and "Wu-Hausman" rows.

Table 6 presents the first-stage regression underlying Table 5, along with two additional exogenous variables: the log of ambient Pb concentrations and the log of annual vehicular Pb density. The latter performs better—its effect is statistically significant at the 99 percent confidence level.

Table 6. First-Stage Results from Independent Variable Regressions

	Dependent variable: annual county average TSP		
	(1)	(2)	(3)
TSP nonattainment status	-10.058***	-9.568***	-7.306***
	(1.790)	(1.909)	(1.809)
log(Lead concentration+1)		8.578	
		(9.666)	
log(Lead density+1)			23.806***
			(8.408)
Age	0.060**	0.038	-0.030
	(0.030)	(0.033)	(0.034)
Parent college	-0.181**	-0.186**	-0.187**
	(0.087)	(0.086)	(0.085)
Median county income	22.369***	21.339***	19.954***
	(0.699)	(1.418)	(1.090)
Cohort	1969–1977	1969–1977	1969–1977
Observations	97,440	97,440	97,440
R2	0.982	0.982	0.983
Adjusted R2	0.982	0.982	0.983

Note: *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level and presented in parentheses. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed.

To disentangle the relative importance of early-life exposure to TSP versus Pb, Table 7 presents the reduced form IV results using the first stage from Model 3 in Table 6. We find that the effects of birth year exposure to TSP are statistically significant at the 99 percent confidence level for conscientiousness and at the 90 percent level for agreeableness and have the same sign as the effects of vehicular Pb density shown in Table 4. The effects of vehicular Pb density in these models, however, is not statistically significant on any personality trait. We note that the standard errors associated with these effects are large, approximately twice those reported in Table 4. We believe that the correlation between Pb density and TSP shown in the first-stage IV model (Table 6) is so high that introducing both the predicted TSP and the vehicular Pb density measure in the second-stage model (Table 7) leads to the weak performance and general insignificance of both measures of environmental quality. Use of ambient Pb concentration instead of Pb density leads to similar results. Put simply, use of Pb density as an instrument for TSP generates too much correlation in the second stage for discriminating results.

Table 7. Instrumental Variable Estimates of the Effects of Early-Life Exposure to TSP and Lead Density on Adult Personality

	Agreeableness	Conscientiousness	Extraversion	Neurotic	Openness
	(1)	(2)	(3)	(4)	(5)
TSP	-0.003*	-0.004***	-0.001	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(Lead density+1)	-0.009	0.084	0.027	0.005	0.076
	(0.079)	(0.077)	(0.074)	(0.086)	(0.093)
Age	0.028***	0.028***	0.008***	-0.026***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.042***	-0.080***	0.020***	-0.046***	0.242***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Median county income	-0.170***	-0.109***	-0.079***	0.203***	0.015
	(0.032)	(0.031)	(0.030)	(0.040)	(0.038)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avgtsp	88.354	88.354	88.354	88.354	88.354
Sdtsp	27.61	27.61	27.61	27.61	27.61
Avglead	1.588	1.588	1.588	1.588	1.588
Sdlead	1.172	1.172	1.172	1.172	1.172
Weak instruments	0	0	0	0	0
Wu-Hausman	0.035	0.003	0.819	0.196	0.017
Observations	97,440	97,440	97,440	97,440	97,440
R^2	0.017	0.089	0.005	0.018	0.026
Adjusted R^2	0.015	0.087	0.003	0.016	0.024

Note: *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level and presented in parentheses. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. TSP emissions are at the county level in the birth year. Lead density is the average estimated lead emissions divided by area of the urban core within the county over the first five years of life (µg /m2). The mean and standard deviation are displayed as “Avglead/tsp” and “Sdlead/tsp.” The p-values of regression diagnostics are presented in the “Weak instruments” and “Wu-Hausman” rows.

8. Conclusion

Reducing Pb exposure continues to be a policy priority. Recent bipartisan infrastructure legislation will "eliminate the nation's lead service lines" and "invest $55 billion to expand access to clean drinking water for households, businesses, schools, and child care centers all across the country," according to The White House, 2021. The US EPA is soliciting comment on a recent revision to the rule on Pb and copper in drinking water and has extended to October 2024 the compliance deadline for the revision finalized in January 2021 (National Primary Drinking Water Regulations, 2021). The agency ordered Benton Harbor, Michigan to take immediate actions to improve safety and reliability of its drinking water (EPA, 2021). In 2018, residents were told to flush their drinking water for five minutes daily to help reduce potential toxins that had been stagnant in lead pipes for extended period (Abdel-Baqui. 2021). The EPA is also evaluating the air quality impact of leaded gasoline used in piston-engine aircraft (EPA 2020; President's Task Force on Environmental Health Risks and Safety Risks to Children, 2018). Seventy percent of Pb in the US atmosphere from leaded fuel are from these aircraft, and Pb exhaust particles are small enough—around 13 nanometers—to penetrate mucosal tissue in the lung and be readily taken up by epithelial cells (Griffith et al. 2020).

This research suggests that young children's environment, including exposures to Pb and airborne particulates, may have subtle subclinical effects on aspects of personality observable to strangers. Our analysis provides the first modeling explicitly linking EPA's regulation of leaded gasoline in the 1970s to personalities of people born from 1969 to 1977 when assessed several decades later. We find that vehicular Pb density in urban core areas during early life predicts adult personality better than ambient Pb concentrations do. In models that treat vehicular Pb emissions as exogenous, it lowers agreeableness and conscientiousness and increases neuroticism and openness. It has no statistically significant effect on extraversion. In addition, vehicular Pb levels in the birth year plus the next four years better predicts adult personality than exposure in the birth year or over 18 years.

Additional research is necessary, however. The nature of the relationship between Pb during early life and adult personality merits additional attention, particularly because it may vary by trait. In addition, our modeling, which controls for both county and cohort fixed effects, may not adequately control for other changes in the early-life environment that occurred in the counties that we studied during the period of our analysis. In particular, modeling of adult personality and TSP suggests that TSP reductions driven by nonattainment with EPA's NAAQS may also affect personalities of adults decades later. More data may be needed to disentangle the separate effects of early-life exposure to Pb and TSP on adult personality.

9. References

Abdel-Baqui, Omar. 2021. Michigan is Suffering From Another Water Crisis, This Time in Benton Harbor, *The Wall Street Journal*. Oct 31, 2021. **https://www.wsj.com/articles/michigan-is-suffering-from-another-water-crisis-this-time-in-benton-harbor-11635686526?st=54aeqzpnjmdd1eu&reflink=article_email_share**

Borghans, L., B. H. Golsteyn, et al. (2016). "What Grades and Achievement Tests Measure." *Proceedings of the National Academy of Sciences* 113(47): 13354–13359.

Chay, K. Y., and Greenstone, M. (2003). The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession. *Quarterly Journal of Economics* 118 (3): 1121–67.

Chay, K. Y., and Greenstone, M. (2005). Does Air Quality Matter? Evidence from the Housing Market. *Journal of Political Economy,* 113(2), 376–424. **https://doi.org/10.1086/427462**

Chay, K., Dobkin, C, and Greenstone, M., (2003). The Clean Air Act of 1970 and Adult Mortality. *Journal of Risk and Uncertainty,* 27(3), 279–300. **http://www.jstor.org/stable/41761166**

Cobb-Clark, D.A., and S. Schurer. 2012. The Stability of Big-Five Personality Traits. *Economics Letters* 115(2): 11–15. **doi:10.1016/j.econlet.2011.11.015**. S2CID 12086995.

Cubel, M., A. Nuevo-Chiquero, S. Sánchez-Pagés, and M. Vidal-Fernandez. 2016. Do Personality Traits Affect Productivity? Evidence from the Laboratory. *The Economic Journal* 126(592) May 2016, 654-681, **https://doi.org/10.1111/ecoj.12373**

Donato, K., G. Miller, M. Mohanan, Y. Truskinovsky, and M. Vera-Hernandez. 2017. Personality Traits and Performance Contracts: Evidence from a Field Experiment Among Maternity Care Providers in India. *American Economic Review* (107)5, 506–510.

Griffith, Jack D. 2020. Electron Microscopic Characterization of Exhaust Particles Containing Lead Dibromide Beads Expelled from Aircraft Burning Leaded Gasoline, *Atmospheric Pollution Research* (11)1481–1486. **https://doi.org/10.1016/j.apr.2020.05.026**

Heckman, J.J., J. Stixrud, et al. 2006. The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics* 24(3): 411–482.

Isen, Adam, Maya Rossin-Slater, and W. Reed Walker. 2017. Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970. *Journal of Political Economy* 125(3), 848–902.

Landrigan, Philip J., Richard Fuller, Nereus J.R. Acosta, Olusoi Adeyi, Robert Arnold, Abdoulaye Bibi Balde, Roberto Bertolini, et al. 2018. The Lancet Commission on Pollution and Health. *The Lancet* 391(10119), 17, 462–512.

Lin, Dajun, Randall Lutter, and Christopher J. Ruhm. 2018. Cognitive Performance and Labour Market Outcomes. *Labour Economics* 15, 121–135. **https://doi.org/10.1016/j.labeco.2017.12.008**

Masters, R., B. Hone, et al., 1998. "Environmental Pollution, Neurotoxicity and Criminal Violence," in *Environmental Toxicology: Current Developments*. J. Rose. Amsterdam, The Netherlands, Gordon & Breach Science Publishers, p. 1-61.

McAdams, D.P. 1995. What Do We Know When We Know a Person? *Journal of Personality* 63: 365–396. **https://doi.org/10.1111/j.1467-6494.1995.tb00500.x**

Murphy, Joshua D. 2017. The Costs, Benefits, and Efficiency of Air Quality Regulation. PhD dissertation, University of Toronto. 88-108 **https://tspace.library.utoronto.ca/bitstream/1807/80811/3/Murphy_Joshua_201711_PhD_thesis.pdf**

New York Times. 1976. Court Backs Curb on Lead in Gasoline. March 19, 1976. **https://www.nytimes.com/1976/03/20/archives/court-backs-curb-on-gasoline-lead-decision-appears-to-uphold-epa.html**. Viewed Nov 10, 2022.

Nevin, R., 2000. "How Lead Exposure Relates to Temporal Changes in IQ, Violent Crime, and Unwed Pregnancy," *Environmental Research*, 83(1), p. 1-22.

Nilsson, Peter. 2009. *The Long Run Effects of Early Childhood Lead Exposure: Evidence from the Phaseout of Leaded Gasoline*. Working paper. Institution of International Economics Studies. **http://www.bristol.ac.uk/media-library/sites/cmpo/migrated/documents/nilsson.pdf**

President's Task Force on Environmental Health Risks and Safety Risks to Children. 2018. Federal Action Plan to Reduce Childhood Lead Exposures and Associated Health Impacts. **https://www.epa.gov/sites/default/files/2018-12/documents/fedactionplan_lead_final.pdf**

Reyes, J. 2007. Environmental Policy as Social Policy? The Impact of Childhood Lead Exposure on Crime. *B.E. Journal of Economic Analysis and Policy* 7(1). **https://jwreyes.people.amherst.edu/papers/LeadCrimeBEJEAP.pdf**

Reyes, J. 2015. Lead Exposure and Behavior: Effects on Antisocial and Risky Behavior among Children and Adolescents. *Economic Inquiry* 53(3). **https://onlinelibrary.wiley.com/doi/10.1111/ecin.12202**

Ruckart PZ, Jones RL, Courtney JG, et al. 2021.“Update of the Blood Lead Reference Value — United States”, *Morb Mortal Wkly Rep* 2021;70:1509–1512. DOI: **http://dx.doi.org/10.15585/mmwr.mm7043a4**

Schwaba, Ted., Wiebke Bleidor, Christopher J. Hopwood, Jochen E. Gebauer, P. Jason Rentfrow, Jeff Potter, and Samuel D. Gosling. 2021. “The Impact of Childhood Lead Exposure on Adult Personality: Evidence from the United States, Europe, and a Large-Scale Natural Experiment”. *Proceedings of the National Academy of Sciences* 118(29) e2020104118

The White House. 2021. Fact Sheet: The Bipartisan Infrastructure Deal, November 6, 2021. **https://www.whitehouse.gov/briefing-room/statements-releases/2021/11/06/fact-sheet-the-bipartisan-infrastructure-deal/** Viewed, Nov 9, 2022.

U.S. Centers for Disease Control and Prevention, Childhood Lead Poisoning Prevention. Undated. “Populations at Higher Risk”, **https://www.cdc.gov/nceh/lead/prevention/populations.htm**. Viewed October 26, 2022.

U.S. Environmental Protection Agency. 2021. National Primary Drinking Water Regulations: Lead and Copper Rule Revisions. 86 *FR* 4198.

U.S. Environmental Protection Agency. 1973. “EPA Requires Phase-Out of Lead in All Grades of Gasoline”. EPA Press Release, November 28, 1973. **https://archive.epa.gov/epa/aboutepa/epa-requires-phase-out-lead-all-grades-gasoline.html**. Viewed Nov 10, 2022.

U.S. Environmental Protection Agency, EPA Office of Policy Analysis. 1985. *Costs and Benefits of Reducing Lead in Gasoline: Final Regulatory Impact Assessment, Environmental Protection Agency*, EPA-230-05-85-006. **https://nepis.epa.gov/Exe/ZyNET.exe/9100YK16.TXT?ZyActionD=ZyDocument&Client=EPA&Index=1981+Thru+1985&Docs=&Query=&Time=&EndTime=&SearchMethod=1&TocRestrict=n&Toc=&TocEntry=&QField=&QFieldYear=&QFieldMonth=&QFieldDay=&IntQFieldOp=0&ExtQFieldOp=0&XmlQuery=&File=D%3A%5Czyfiles%5CIndex%20Data%5C81thru85%5CTxt%5C00000021%5C9100YK16.txt&User=ANONYMOUS&Password=anonymous&SortMethod=h%7C-&MaximumDocuments=1&FuzzyDegree=0&ImageQuality=r75g8/r75g8/x150y150g16/i425&Display=hpfr&DefSeekPage=x&SearchBack=ZyActionL&Back=ZyActionS&BackDesc=Results%20page&MaximumPages=1&ZyEntry=1&SeekPage=x&ZyPURL**

U.S. Environmental Protection Agency. 2013. *Integrated Science Assessment for Lead*. Research Triangle Park, NC: National Center for Environmental Assessment-RTP Division, Office of Research and Development, US Environmental Protection Agency.

U.S. Environmental Protection Agency. 2020. Data and Analysis of Piston-Engine Aircraft Emissions of Lead at US Airports. **https://www.epa.gov/regulations-emissions-vehicles-and-engines/epas-data-and-analysis-piston-engine-aircraft-emissions**

U.S. Environmental Protection Agency, Press Release. 2021. EPA Directs City of Benton Harbor, Michigan, to Take Immediate Actions to Improve the Safety and Reliability of its Drinking Water. **https://www.epa.gov/newsreleases/epa-directs-city-benton-harbor-michigan-take-immediate-actions-improve-safety-and**. Viewed Nov. 2, 2021.

Appendices

Appendix 1. EPA's Actions to Regulate TSP and Lead from Motor Vehicles During the 1970s

A1.1. TSP

—EPA established NAAQS for the criteria pollutants, including TSP, on April 20, 1971 (36 *FR* 8186).

—Section 110 required states to prepare and submit for EPA approval plans within nine months after EPA established NAAQS. State plans were to include the designation of AQCRs as attainment or nonattainment areas. On August 14, 1971, EPA published a final notice (36 *FR* 15486) setting out its requirements for the preparation, adoption, and submittal of state plans.

—State plans were submitted in early 1972—as of May 31, 1972, all states had submitted plans (although some were incomplete) (37 *FR* 10842).

—On May 31, 1972, EPA published a notice approving the states' plans, including designations—or disapproving parts of the plans and requiring revisions or additional provisions where it determined a plan was inadequate (e.g., EPA required Colorado to add transportation control measures) (37 *FR* 10842).

—State plans were required under the CAA requirements to provide for attainment of the NAAQS within three years from the date of EPA approval (although EPA could also grant an extension of up to two years under the CAA). It is unlikely that sources would immediately achieve significant reductions in their PM emissions in 1972 or 1973—required levels of control would likely be achieved only over subsequent years to meet the 1975 deadline. The May 31, 1972, final rule indeed stated that "it is already clear, however, that the aggregate emission control requirements of the 55 state plans will create such a great demand for clean fuels, emission control equipment, and other items that attainment of the primary standards in many urban areas in significantly less time than 3 years generally will not be feasible" (37 *FR* 10843).

A1.2. Lead

EPA was also active in lowering the lead (Pb) content of gasoline beginning in 1971, before its well-known actions to eliminate it during the Reagan administration.

1. January 1971: EPA administrator Ruckelshaus declared that "an extensive body of information exists which indicates that the addition of alkyl lead to gasoline…results in lead particles that pose a threat to public health."

2. EPA's first rule, issued January 10, 1973 (EPA, 1973): EPA required the general availability of one grade of unleaded gasoline by July 1, 1974 (required for catalysts controlling HC tailpipe emissions). EPA also reproposed a phasedown schedule for leaded gasoline, with a final limit of 1.25 g/gallon by January 1, 1978.

3. EPA's 2nd rule (December 1973): EPA limited Pb content per gallon averaged over all gasoline (leaded and unleaded) at the refinery according to the following phasedown schedule:

- July 1, 1975: 1.7 g/gal
- July 1, 1976: 1.2 g/gal
- July 1, 1977: 0.9 g/gal
- July 1, 1977: 0.6 g/gal

The final rule also provided a two-year delay (until July 1977) of the scheduled phasedown for small refiners (EPA, 1973).

4. Judicial support: The federal DC Circuit Court in March 20, 1976, upheld EPA's rule shifting the scheduled reductions to begin in 1976, to phase down to 0.6 g/gal in 1979. (New York Times, 1976).

Appendix 2. A Novel Measure of Lead Emissions from Gasoline

We present a measure of lead (Pb) emissions from motor vehicle gasoline that is novel relative to existing measures because it varies by county and year. It may prove to be a measure of emissions relevant to exposure that is more accurate and useful than other measures used.

Our measure by county *i*, in year *t*, is expressed as kilos of Pb emitted from cars and trucks using gasoline, per square kilometer, $Pb_{i,t}$. We find data to construct this measure starting in 1970 and ending in 1982, after the phaseout was complete.

Data Sources. We use the following data:

1. Quantity sold in gallons, by month and grade, or leaded and unleaded fuel, by state and for DC.
    a. Ethyl Corporation (Petroleum Chemicals Division) provides these data in its Yearly Report of Gasoline Sales: By States. We found only a hard copy.

b. These data start in 1970 and run to 1982. The yearly report provides quantity sold of leaded and unleaded premium and nonpremium. The first year of data on unleaded gasoline sales volume is 1975; it made no distinction between unleaded premium and unleaded regular. Sales volume data for both unleaded premium and unleaded nonpremium first appear in 1981.

c. Data revisions appear in the Report of Gasoline Sales for the following year (Table A2.1).

2. Pb content of gasoline (grams per gallon) by grade (premium, regular, unleaded), for each marketing district, which cover the country, by season (summer = J,J,A; winter = D,J,F).

    a. The source is DOE Bartlesville Energy Research Center. The reports appear twice each year, for winter and summer.

    b. Thirty-two states plus DC fall entirely within these 17 marketing districts. We assign all counties in each of these 32 states (and DC) to the appropriate marketing district.

    c. We assign counties in the remaining 16 contiguous states to one or more marketing districts after a detailed review of their boundaries. See Table A2.2 for these 16 states and Figure 1 for a map of the 17 marketing districts. We determine assignments for these counties based on feasibility using case-by-case criteria.

3. EPA's annual National Emissions Report (of National Emissions Data System), beginning in 1972) provides nitrogen oxide (NOx) emissions by state and AQCRs that cover all counties in all states.

    a. When a single AQCR covers parts of multiple states, the National Emissions Report provides NOx emissions data for that AQCR by state. Thus, the AQCR for the DC metropolitan area has NOx emissions reported for MD, VA, and also DC.

    b. Many of these data are described as "preliminary" or still subject to validation by the state. We are unaware of a publicly available report of these data that is not described as "preliminary."

    c. Murphy (2017) (based on 37 *FR* 10841) indicates that all AQCRs contain only whole counties. We assign counties to AQCRs using data from Murphy (2017), but also validate the data by comparing them with the *FR* notice.

4. County and state-level data on population, by year

a. Census data on county populations by calendar year since 1969 are available at **https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-detail.html**.

5. County and state-level data on geographic size, in square kilometers.

Computations. We construct our measure of county-level lead emissions from motor vehicles by taking the following steps:

1. State-level Pb emissions from motor vehicles.

   a. For the 32 states (including DC) that are entirely within a marketing district, we compute each state's Pb emissions from gasoline used for motor vehicles (in year t) as PB_s, where

   $PB_s = \sum_g \sum_m \{(\text{gallons sold in State S, of grade g in month m}) \times$

   $(Pb \text{ content of grade g, in district D, in month m, in grams per gallon})\}$

   We suppress the time subscript for simplicity. For spring months (March, April, May) and fall (September, October and November), we assume the Pb content can be approximated by a linear interpolation. For winter, we assume the Pb content is unchanged in December to February, and for summer, we assume it is unchanged from June through August.

   b. For the other 17 contiguous states (including DC), we make case-by-case determinations about how to estimate proxies for state-level Pb emissions from motor vehicles.

2. Apportionment of state-level Pb emissions from motor vehicles to individual counties.

   a. We first assign each county to

      i. An AQCR and

      ii. One of 17 marketing districts, if feasible, noting that some counties are split by boundaries between marketing districts.

   b. We define an AQCR's share of a state's annual motor vehicle lead emissions, as $S_{A,s}$, where *A* identifies the AQCR and *s* identifies the state.

i. We assume it can be approximated by the AQCR's share of the state's total motor vehicle NO_x emissions, from EPA's annual National Emissions Reports.

c. We define a county's share of an AQCR's motor vehicle Pb emissions as $S_{i,A}$, where *i* identifies the county, and *A* identifies the AQCR (or for multistate AQCRs, the portion within the same state as the county *i*).

i. We assume it can be approximated in a specific year by that county's share of the population of the AQCR (or, for multistate AQCRs, the portion within the same state as the county *i*).

d. We compute each county's share of the state's Pb emissions as $S_{i,s} = S_{i,A} / S_{A,s}$

3. Synthesis: we calculate motor vehicle Pb emissions by county PB_i, as

a. $PB_i = PB_s S_{i,A} / S_{A,s}$, and then divide by the size of the county in square kilometers, to derive PB_i^e; where the superscript *e* denotes our emissions estimate expressed per square kilometer so as to be interpretable as a proxy for exposure. We also develop an "adjusted" measure of Pb density, defined as micrograms of vehicular Pb emissions per square meter of urban core within the county.

Table A1. Gasoline Volume Sold: Data Availability

Year	Leaded Premium	Leaded Regular	Unleaded	Comment
1970	1	1	No data tables exist	Revisions are in a separate file.
1971	1	1		
1972	1	1		
1973	1	1		
1974	1	1		No table of revisions exists.
1975	1	1	1	
1976	1	1	1	
1977	1	1	1	
1978	1	1	1	
1979	1	1	1	
1980	1	1	1	
1981	1	1	Unleaded premium and unleaded regular are two tables.	

Note: We use “1” to indicate that data are available.

Source: Ethyl Corporation

Table A2. Marketing Districts and State Boundaries

Marketing districts	Complete states	Partial states	Comments
1	VT, NH, ME, MA	NY	
2	RI, CT, DC, DE, VA, WV	NY, PA, MD	NY and PA are split diagonally. MD panhandle is split diagonally.
3	NC, SC, GA, FL, AL	TN	
4	OH	MD, NY, PA, KY, WV	NY and PA are split diagonally. MD panhandle is split diagonally.
5	MI		
6	WI	IA, IL, IN	
7		IL, IN, KY, (eastern) MO	
8	LA, MS	AR, TN	AR is split diagonally.
9	ND, SD, MN		
10	NE	IA, KS, MO	
11		AR, KS, MO, OK, TX	AR is split diagonally.
12		TX	
13	AZ, CO, NVA, NM, UT	CA, KS, OK, TX	CA has curved boundaries for marketing district #13.
14	ID, MT, WY	WA, OR	
15		WA, OR	
16		CA	CA has curved boundaries for marketing district #16.
17		CA	CA has curved boundaries for marketing district #17.

Figure A1. Map showing locations and numbers of samples by areas and locations.

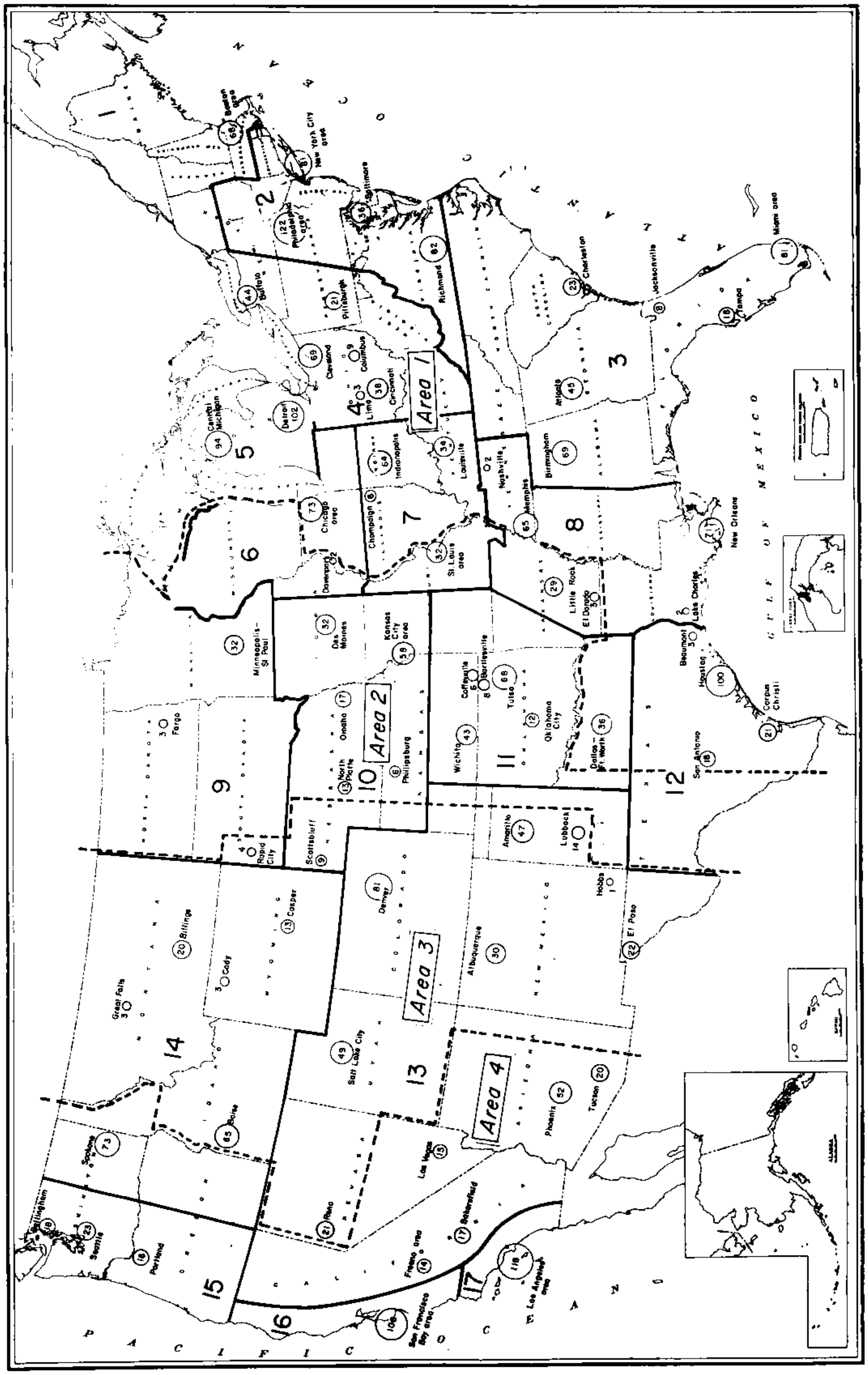


FIGURE 15.– Map showing locations and numbers of samples by districts and areas for the national motor gasoline survey, summer 1977

Appendix 3. Additional Statistical Analyses

Table A3. Summary Statistics

Panel A: Full Sample (250 counties, 132,383 observations)

Variable	Mean	SD	Min	Max
Agreeableness	3.798	0.680	1.000	5.000
Conscientiousness	3.759	0.704	1.000	5.000
Extraversion	3.310	0.860	1.000	5.000
Neuroticism	2.850	0.838	1.000	5.000
Openness	3.725	0.678	1.000	5.000
Year of birth	1973	2.585	1969	1977
Age when taking survey	36.500	4.265	26.000	46.000
Parents college graduates	0.636	0.481	0.000	1.000
Current college student	0.186	0.389	0.000	1.000
County median household income/10,000	5.450	1.180	3.113	9.724
Average county lead concentration in the first 5 years (μg /m^3)	0.987	0.538	0.000	2.949
Average county lead density in the first 5 years (μg /m^2)	1.459	1.098	0.000	9.041

Panel B: TSP Balanced Sample (160 counties, 97,440 observations)

Variable	Mean	SD	Min	Max
Agreeableness	3.798	0.681	1.000	5.000
Conscientiousness	3.761	0.707	1.000	5.000
Extraversion	3.316	0.859	1.000	5.000
Neuroticism	2.849	0.840	1.000	5.000
Openness	3.730	0.677	1.000	5.000
Year of birth	1973	2.595	1969	1977
Age when taking survey	36.550	4.267	26.000	46.000
Parents college graduates	0.631	0.483	0.000	1.000
Current college student	0.187	0.390	0.000	1.000
County median household income/10,000	5.412	1.050	3.113	8.228
Average county lead concentration in the first 5 years ($\mu g/m^3$)	1.029	0.567	0.000	2.949
Average county lead density in the first 5 years ($\mu g/m^2$)	1.588	1.172	0.000	9.041

Appendix 4. Statistical Analyses

Table A4.1. Effects of Early-Life Lead on Adult Agreeableness

	Dependent variable: Agreeableness				
	(1)	(2)	(3)	(4)	(5)
log(Lead concentration+1)	-0.032	-0.022*	-0.082***		
	(0.029)	(0.013)	(0.026)		
log(Lead density (unadj)+1)				-0.074*	
				(0.044)	
log(Lead density (adj)+1)					-0.124***
					(0.035)
Age	0.026***	0.026***	0.027***	0.026***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.014***	-0.014***	-0.040***	-0.040***	-0.040***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Median county income	-0.161***	-0.161***	-0.247***	-0.252***	-0.222***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.014)
Time frame	18 years	5 years	5 years	5 years	5 years
Cohort	All	All	1969–1977	1969–1977	1969–1977
Avglead	0.181	0.433	0.987	0.507	1.459
Sdlead	0.326	0.571	0.538	0.916	1.098
Observations	1,059,813	1,059,813	132,383	132,383	132,383
R^2	0.014	0.014	0.018	0.018	0.018
Adjusted R^2	0.014	0.014	0.016	0.016	0.016

Note: Standard errors are clustered at the county level. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the specified time frame (µg /m^3). Lead density is the average estimated lead emissions divided by area within the county over the specified time frame (µg /m^2). The mean and standard deviation of relevant lead measures (without transformations) are displayed as “Avglead” and “Sdlead.”

Table A4.2. Effects of Early-Life Lead on Adult Conscientiousness

	Dependent variable: Conscientiousness				
	(1)	(2)	(3)	(4)	(5)
log(Lead concentration+1)	-0.011	0.011	-0.036		
	(0.048)	(0.021)	(0.033)		
log(Lead density (unadj)+1)				-0.008	
				(0.042)	
log(Lead density (adj)+1)					-0.066**
					(0.030)
Age	0.046***	0.046***	0.027***	0.027***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.010***	-0.010***	-0.078***	-0.078***	-0.078***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Median county income	-0.288***	-0.287***	-0.160***	-0.162***	-0.147***
	(0.005)	(0.005)	(0.010)	(0.010)	(0.013)
Time frame	18 years	5 years	5 years	5 years	5 years
Cohort	All	All	1969–1977	1969–1977	1969–1977
Avglead	0.181	0.433	0.987	0.507	1.459
Sdlead	0.326	0.571	0.538	0.916	1.098
Observations	1,059,813	1,059,813	132,383	132,383	132,383
R^2	0.067	0.067	0.091	0.091	0.091
Adjusted R^2	0.066	0.066	0.089	0.089	0.089

Note: Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the specified time frame (µg /m^3). Lead density is the average estimated lead emissions divided by area within the county over the specified time frame (µg /m^2). The mean and standard deviation of relevant lead measures (without transformations) are displayed as “Avglead” and “Sdlead.”

Table A4.3. Effects of Early-Life Lead on Adult Extraversion

	Dependent variable: Extraversion				
	(1)	(2)	(3)	(4)	(5)
log(Lead concentration+1)	0.160***	0.065***	0.056**		
	(0.026)	(0.023)	(0.028)		
log(Lead density (unadj)+1)				0.069	
				(0.055)	
log(Lead density (adj)+1)					0.021
					(0.034)
Age	-0.005***	-0.005***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	0.047***	0.047***	0.019***	0.020***	0.020***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
Median county income	-0.009**	-0.009**	-0.039***	-0.036***	-0.041***
	(0.004)	(0.004)	(0.010)	(0.010)	(0.012)
Time frame	18 years	5 years	5 years	5 years	5 years
Cohort	all	all	1969–1977	1969–1977	1969–1977
Avglead	0.181	0.433	0.987	0.507	1.459
Sdlead	0.326	0.571	0.538	0.916	1.098
Observations	1,059,813	1,059,813	132,383	132,383	132,383
R^2	0.003	0.003	0.006	0.006	0.006
Adjusted R^2	0.003	0.003	0.004	0.004	0.004

Note: Standard errors are clustered at the county level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the specified time frame (µg /m^3). Lead density is the average estimated lead emissions divided by area within the county over the specified time frame (µg /m^2). The mean and standard deviation of relevant lead measures (without transformations) are displayed as "Avglead" and "Sdlead."

Table A4.4. Effects of Early-Life Lead on Adult Neuroticism

	Dependent variable: Neuroticism				
	(1)	(2)	(3)	(4)	(5)
log(Lead concentration+1)	-0.030	0.002	0.024		
	(0.036)	(0.021)	(0.030)		
log(Lead density (unadj)+1)				-0.046	
				(0.043)	
log(Lead density (adj)+1)					0.068**
					(0.032)
Age	-0.016***	-0.016***	-0.025***	-0.025***	-0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.059***	-0.059***	-0.048***	-0.048***	-0.048***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Median county income	0.121***	0.121***	0.210***	0.211***	0.195***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.014)
Time frame	18 years	5 years	5 years	5 years	5 years
Cohort	all	all	1969–1977	1969–1977	1969–1977
Avglead	0.181	0.433	0.987	0.507	1.459
Sdlead	0.326	0.571	0.538	0.916	1.098
Observations	1,059,813	1,059,813	132,383	132,383	132,383
R^2	0.010	0.010	0.018	0.018	0.018
Adjusted R^2	0.009	0.009	0.016	0.016	0.016

Note: Standard errors are clustered at the county level. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the specified time frame ($\mu g / m^3$). Lead density is the average estimated lead emissions divided by area within the county over the specified time frame ($\mu g / m^2$). The mean and standard deviation of relevant lead measures (without transformations) are displayed as “Avglead” and “Sdlead.”

Table A4.5. Effects of Early-Life Lead on Adult Openness

	Dependent variable: Openness				
	(1)	(2)	(3)	(4)	(5)
log(Lead concentration+1)	-0.002	0.005	0.055*		
	(0.021)	(0.013)	(0.029)		
log(Lead density (unadj)+1)				0.145***	
				(0.056)	
log(Lead density (adj)+1)					0.183***
					(0.039)
Age	-0.002***	-0.002***	-0.012***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	0.158***	0.158***	0.248***	0.248***	0.248***
	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)
Median county income	-0.026***	-0.026***	0.053***	0.056***	0.012
	(0.004)	(0.004)	(0.009)	(0.009)	(0.012)
Time frame	18 years	5 years	5 years	5 years	5 years
Cohort	all	all	1969–1977	1969–1977	1969–1977
Avglead	0.181	0.433	0.987	0.507	1.459
Sdlead	0.326	0.571	0.538	0.916	1.098
Observations	1,059,813	1,059,813	132,383	132,383	132,383
R^2	0.016	0.016	0.027	0.027	0.028
Adjusted R^2	0.016	0.016	0.025	0.025	0.026

Note: Standard errors are clustered at the county level. *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the specified time frame (µg /m³). Lead density is the average estimated lead emissions divided by area within the county over the specified time frame (µg /m²). The mean and standard deviation of relevant lead measures (without transformations) are displayed as "Avglead" and "Sdlead."

Table A4.6. Effects of Early-Life Exposure to Ambient Lead Emissions Density on Adult Personality Traits: Linear Models

	Agr	Con	Ext	Neu	Ope
	(1)	(2)	(3)	(4)	(5)
Lead concentration	-0.034***	-0.009	0.027**	0.011	0.019*
	(0.011)	(0.014)	(0.012)	(0.013)	(0.012)
Age	0.027***	0.027***	0.008***	-0.025***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.040***	-0.078***	0.019***	-0.048***	0.248***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Median county income	-0.250***	-0.162***	-0.038***	0.211***	0.055***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.009)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avglead	0.987	0.987	0.987	0.987	0.987
Sdlead	0.538	0.538	0.538	0.538	0.538
Observations	132,383	132,383	132,383	132,383	132,383
R^2	0.018	0.091	0.006	0.018	0.027
Adjusted R^2	0.016	0.089	0.004	0.016	0.025

Note: *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level and presented in parentheses. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead concentration is the arithmetic mean of non-zero monitor readings within the county over the first five years of life (µg/m^3). The mean and standard deviation are displayed as “Avglead” and “Sdlead.”

Table A4.7. Effects of Early-Life Exposure to Vehicular Lead Emissions Density on Adult Personality Traits: Linear Models

	Agr	Con	Ext	Neu	Ope
	(1)	(2)	(3)	(4)	(5)
Lead concentration	-0.021**	0.002	0.012	0.001	0.047***
	(0.010)	(0.008)	(0.010)	(0.009)	(0.010)
Age	0.027***	0.027***	0.008***	-0.025***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parent college	-0.040***	-0.078***	0.020***	-0.048***	0.248***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Median county income	-0.243***	-0.163***	-0.041***	0.211***	0.036***
	(0.011)	(0.011)	(0.010)	(0.012)	(0.010)
Cohort	1969–1977	1969–1977	1969–1977	1969–1977	1969–1977
Avglead	1.459	1.459	1.459	1.459	1.459
Sdlead	1.098	1.098	1.098	1.098	1.098
Observations	132,383	132,383	132,383	132,383	132,383
R^2	0.018	0.091	0.006	0.018	0.027
Adjusted R^2	0.016	0.089	0.004	0.016	0.026

Note: *p < 0.1; **p < 0.05; ***p < 0.01. All regressions include county and five-year cohort fixed effects. Standard errors are clustered at the county level and presented in parentheses. Counties with smelters or in Alaska, Hawaii, and Puerto Rico are removed. Lead density is the average estimated lead emissions divided by area within the county over the first five years of life (µg /m^2). The mean and standard deviation are displayed as “Avglead” and “Sdlead.”