Long-Run Environmental Accounting in the U.S. Economy.

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Abstract

This paper estimates an augmented measure of national output inclusive of environmental pollution damage in the United States economy over a 60-year period. The paper reports two primary findings. First, air pollution intensity declined precipitously from the 1950s to the modern era. Air pollution damage comprised roughly 30 percent of output in the post WWII economy, declining to under 10 percent in 2016. Second, accounting for pollution damage significantly affects growth rates. Prior to the passage of the Clean Air Act in 1970, GDP outpaced Environmentally-Adjusted Value Added (EVA), defined as GDP less air pollution damage. Following passage of the Act, EVA grew more rapidly than GDP. Macroeconomic and environmental policies, as well as the business cycle, appreciably affect damages and EVA growth.

Keywords: Environmental accounting, air pollution, national income and product accounts, value of a statistical life, business cycle.

JEL Codes: E01, Q56, Q53, E21, N32, N52.

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I. Introduction.

Among the fundamental advances in the field of economics during the 20th century was the invention and deployment of the National Income and Product Accounts (NIPAs). Importantly, for nearly as long as the NIPAs have existed, economists have known that the accounts are incomplete. Excluded are phenomena beyond the market boundary. Principal among these are leisure time, home production, and the environment (Nordhaus and Tobin, 1972).

This paper zeros in on the last category of omissions: environmental services. Efforts to encompass this dimension, often referred to as environmental accounting, augment the NIPAs by encompassing the value of natural resources in situ and the monetary costs due to environmental damage (NAS NRC, 1999; Abraham and Mackie, 2006; Nordhaus, 2006; Muller, Mendelsohn, Nordhaus, 2011). When appropriately coupled with the NIPAs, environmental accounts provide a more comprehensive measure of the condition of an economic system.

Within the broad environmental accounting context, this analysis focuses on air pollution damage. Prior research demonstrates that, in the cross-section, or over short time periods, accounting for pollution damage appreciably affects estimates of the level of output and growth (Bartelmus, 2009; Muller, Mendelsohn, Nordhaus, 2011; Muller, 2014). In contrast to extant research, this analysis reports pollution damage from the middle of the 20th century to the present day. This long run perspective enables an assessment of the implications of relying on market indices for inferences about the growth and development of the U.S. economy. Further, both neoclassical economic growth models and macro-environmental impact models implicitly make the case for long-run analyses. Neoclassical models argue that long run growth depends critically on the capital stock, population growth, and technological change (Solow, 1956; Baumol, 1986; Romer, 1990). Macro characterizations of environmental impact tend to emphasize the importance of population size, income (because this influences the energy intensity of production and consumption) and technology (Ehrlich and Holdren, 1971; Chertow, 2001). These two classes of models motivate studying environmental accounts over a long time period in the following sense. Both income and population in an economic system tend not to change drastically over short time periods: say, less than five years. Growth in the capital stock (either widening or deepening) does not occur rapidly. Further, fundamental technological advances occur in fits and starts. The penetration of fundamental innovations into various economic sectors and household often takes years (Gordon, 2016). Hence, long time horizons are often required to study changes in environmental impact and growth. In addition, the data used herein show that fine particulate matter concentrations fell from an average of over 50 ug/m^3 in 1957 to under 10 ug/m^3 in 2016.

Historical data is used herein to develop a 61-year series of Gross External Damage (GED), (Muller, Mendelsohn, and Nordhaus, 2011; Muller, 2014), a macroeconomic environmental indicator, encompassing air pollution emissions from all sectors in the United States (U.S.) economy. This dimension of environmental accounting (as opposed to, say, water pollution) features excellent data availability and the potential to appreciably affect estimates of comprehensive consumption (NAS NRC, 1999; Muller, 2013; 2014).

To estimate air pollution damage over this 61-year time horizon, several sources of pollution data are used. From 1980 to 2016, annual average fine particulate matter ($PM_{2.5}$) estimates provided by Meng et al., (2019) are used. These data are resolved at 1^o latitude-longitude grid-cells and they provide universal coverage of the contiguous U.S. In contrast, United States Environmental Protection Agency (USEPA) monitors for $PM_{2.5}$ have only been operational since 1999. The monitors provide only sparse spatial coverage. The agreement between the satellite data and monitor readings between 1999 and 2016 is quite strong (see figure A.1). From 1979 back to 1957, the data are drawn from historical monitoring sites (Clay et al., 2019). Specifically, the early network of monitors measured total suspended particulates (TSP). The analysis uses regression models to calculate $PM_{2.5}$ (which is a subset of TSP) levels from the TSP readings. The spatial extent of this network was quite thin. As such from 1957 to 1980, the paper only reports national results. When spliced together with the satellite data the analysis obtains a continuous time series from 1957 to 2016 consisting of national scale, annual average $PM_{2.5}$.

The prior environmental accounting literature suggests that the total, or gross, damage is the product of emissions and marginal damage (Nordhaus, 2006; Muller, Mendelsohn, Nordhaus, 2011). This is conceptually consistent with how GDP is measured: prices of products are multiplied times the quantity produced to compute total value. Because of data and modeling limitations, this analysis computes damages in a slightly different fashion. Consider ambient pollution estimates in a given location, say, Pennsylvania, and year, perhaps 1992. The paper computes consequences from exposure to pollution levels in Pennsylvania in 1992 using population counts, mortality rates, and estimated $PM_{2.5}$. Intuitively, $PM_{2.5}$ levels are the sum of contributions from a multitude of sources distributed across space, upwind from said locality. Note that this approach attributes damages to the location of *exposure*, not the location of *emissions*. The parallel with the NIPAs is the following: while GDP values production and allocates value to the location of output, measures such as personal consumption expenditure (PCE) ascribe value to where consumption of goods and services occurs. The former tracks with valuation of pollution emissions. The latter is analogous to valuing damage from exposure.

At an aggregate, national scale, the difference between valuing emissions and valuing concentrations should be negligible. However, for sub-national accounting (which this analysis executes for 1980 to 2016) the appropriate treatment of monetary damages computed from exposure in this way is a deduction from (market) consumption within the jurisdiction where exposure occurs (Muller, Matthews, Wiltshire-Gordon, 2017; Jha, Matthews, Muller, 2019). That is, without the ability to attribute concentrations, exposures, and damages spatially to specific sources, industries, or sectors, the integration with the NIPAs occurs through consumption expenditures. It would be an inappropriate conflation to deduct exposure-based GED in a particular jurisdiction from emitting sources in that jurisdiction because of the natural flows of pollution in the natural environment. Emissions cross geo-political lines.

Given these considerations, pollution costs are deducted from the market accounts (Abraham and Mackie, 2006; Nordhaus, 2006; Muller, Mendelsohn, Nordhaus, 2011; Muller, 2014). Nationally, the GED are deducted from GDP for the full 61-year time series. For the state level analysis (from 1980 to 2016), the GED are subtracted from PCE. Year-over-year growth is calculated in the GDP-GED measure and this is compared to GDP growth. For the state level analysis, growth is estimated in PCE-GED and this is benchmarked against PCE growth on an annual basis.

Prior research has shown that air pollution damage is primarily composed of premature mortality risk (USEPA, 1999; 2011; Muller and Mendelsohn, 2007; Muller, Mendelsohn, Nordhaus, 2011). Hence, human exposure is a key determinant of damage. Because of this, and recognizing data limitations due to the historical context[1], the present paper focuses only on mortality risks due to exposure to $PM_{2.5}$. Equipped with ambient concentration estimates, the analysis uses standard damage-function techniques to translate $PM_{2.5}$ exposure into monetary damage. Peer-

[1] For example, obtaining incidence rates for illnesses may not be possible for early years in the sample.

reviewed adult mortality concentration-response functions (Krewski et al., 2009) link exposure to mortality risk. The Value of a Statistical Life (VSL) approach then translates mortality risk into monetary units (Viscusi and Aldy, 2003).

The application of standard damage function techniques to historic data generates concerns in two areas. First, utilizing results from epidemiological studies conducted in the modern era to exposures in the middle of the 20th century introduces considerable uncertainty into the empirical damage estimates reported herein. However, the earliest cohort from the Harvard Six Cities study included exposures as early as 1974 (Laden et. al., 2006). Hence, any issues associated with inappropriate extrapolation of the epidemiological results likely manifests in the earliest years of the 61-year timeframe explored here; exposure levels were apparently starkly higher than in the modern era.

Second, most estimates of the VSL are derived from labor market data or contingent valuation surveys results from the last, say, 40 years. This motivates a search of the literature for VSL estimates from the middle of the 20th century. Costa and Kahn (2004) provide such estimates. Specifically, Costa and Kahn (2004) report decadal VSLs derived from labor market data from 1940 to 1980. From 1980 forward to 2016, the paper couples the US Bureau of Economic Analysis' real personal income series, with VSL-income elasticities reported in the literature, and the USEPA's default VSL (Costa, Kahn, 2004; Hammitt, Robinson, 2011; USEPA, 2011). Figure A.3 in the appendix displays the VSLs from 1957 to 2016.

Results are organized into three areas: national scale findings spanning the full 1957 to 2016 time series, state results from 1980 to 2016, and output from a series of regression analyses conducted on the 1980 to 2016 state-level series that explores determinants of growth. The national analysis indicates that during the late 1950s and early 1960s, pollution damages comprised a staggering share of national output. The GED amount to between roughly 30 and 40 percent of GDP. The GED-to-GDP ratio falls to just under 10 percent of GDP in 2016. From 1957 to 2016, the GDP-GED metric grew roughly one-half of a percentage point more rapidly than GDP. Prior to passage of the Clean Air Act and other landmark environmental policies in the early 1970's, growth in GDP exceeded that of the augmented measure. From 1970 onward, the augmented measure outpaced GDP. A series of descriptive regressions argue that the business cycle is a critical factor in determining the difference in pollution-adjusted versus GDP growth. Finally, Title I of the Clean Air Act significantly attenuated GED and boosted pollution-adjusted growth.

The remainder of the paper is structured as follows. Section II presents a conceptual framework based on the NIPAs for the deduction of environmental pollution damage from the market accounts. Section III focuses on methods and data sources. Section IV. reports the results and V. concludes.

II. Conceptual Model.

This section uses a national income accounting framework to explore differences in growth characterized by the market accounts and accounts augmented with environmental pollution damage and expenditures on pollution removal. The modeling begins with a pre-policy economy with zero abatement to reflect the historical focus of the paper. The model then incorporates investment in pollution control. The key results from the conceptual modeling section are as follows. First, in the pre-policy economy, mismeasurement of growth depends only on the trajectory of damage. Falling damages boosts growth, while rising damages dampens growth in the augmented index. There is no mismeasurement of growth when damages change at the same rate as market consumption. Second, with pollution policy, the intertemporal changes in abatement and damage together determine the difference in market and augmented growth. Both damages and investments in abatement place a drag on consumption growth. As such, the sensitivity of pollution damage to abatement is the key in determining whether augmented consumption grows more or less rapidly than the market accounts.

Market output, or GDP, denoted (Y_t^m) is expressed in terms of the standard accounting identity as shown in (1).

$$Y_t^m = C_t + I_t + G_t + X_t \tag{1}$$

where:

C_t = consumption of market goods during time (t).
$I_t = K_t - \lambda K_{t-1}$: net investment in physical capital, where λ is the depreciation of physical capital.
G_t = government expenditure.
X_t = net exports.

Abatement and damage in time period (t) are modeled as a deduction from consumption in period (t). Let A_t represent expenditure on abatement of pollution: $A_t = \gamma_t C_t$, where $(0 \leq \gamma_t \leq 1)$. Further, let (D_t) reflect pollution damage, or degradation of natural capital: $D_t = \alpha_t C_t - \beta_t(\gamma_t C_t)$. The autonomous[2] pollution-intensity of output is given by (α), while (β) reflects the sensitivity of environmental damage to investment in abatement. As such, damage falls with increasing abatement effort (γ_t), with greater responsiveness of damage to abatement (β), and it rises with more pollution intensive output (Muller, 2019).

2 Autonomous pollution intensity is defined as the pollution damage per unit output prior to abatement.

Expression (2) proposes this alternative characterization of national output.

$$Y_{t+1}^{e} = C_{t+1}\big(1-\gamma_{t+1}-(\alpha_{t+1}-\beta_{t+1}\gamma_{t+1})\big)+I_t+G_t+X_t \tag{2}$$

a. Augmented Accounts in a "Pre-Policy" Economy.

Because this paper's focus is explicitly historical, and in early stages of development, abatement of pollution (the provision of environmental public goods) is likely to be at or near zero, the model begins in a situation with zero abatement. In this "pre-policy" economy, growth in the augmented index (which, importantly, features an augmentation only consisting of damages) is shown in (3):

$$\frac{Y_{t+1}^{e}-Y_t^{e}}{Y_t^{e}} = \frac{Y_{t+1}^{m}-Y_t^{m}+\big(C_t(\alpha_t)-C_{t+1}(\alpha_{t+1})\big)}{Y_t^{e}} \tag{3}$$

Expression (3) reveals that the intertemporal change in damage $\big(C_t(\alpha_t)-C_{t+1}(\alpha_{t+1})\big)$ is a key driver in the augmented growth rate. Rising (falling) damages attenuate (enhance) growth. Consider the following cases. If pollution intensity remains fixed, $(\alpha_t)=(\alpha_{t+1})$, damages rise if consumption rises. If pollution-intensity increases and consumption increases, remains constant, or falls by less than pollution intensity increases, damages also increase. Hence, falling damages are most likely to occur during contractionary periods and during periods when autonomous pollution intensity falls precipitously[3]. Further, since damage in period (t) lowers (Y_t^e), higher initial levels of damage enhance the growth rate.

[3] Note that, by construction, these periods do not correspond to more stringent environmental policy. Rather, the convenience-driven transitions from coal-based home heating to the use of natural gas is an example of a large change in autonomous pollution-intensity.

In the pre-policy economy with zero abatement, the difference between growth in the market index and growth in the augmented accounts reduces to (4):

$$\frac{Y_{t+1}^{e}-Y_{t}^{e}}{Y_{t}^{e}}-\frac{Y_{t+1}^{m}-Y_{t}^{m}}{Y_{t}^{m}}=\frac{C_{t}(\alpha_{t})}{Y_{t}^{e}}\left(\frac{Y_{t+1}^{m}}{Y_{t}^{m}}\right)-\frac{C_{t+1}(\alpha_{t+1})}{Y_{t}^{e}} \tag{4}$$

The difference in growth rates is a simple expression of GDP growth $\left(\frac{Y_{t+1}^{m}}{Y_{t}^{m}}\right)$ and the damage intensity of output. This expression again emphasizes the importance of the intertemporal change in damage to growth in the augmented metric. Setting (4) to zero and rearranging produces: $\frac{Y_{t+1}^{m}}{Y_{t}^{m}}=\frac{C_{t+1}(\alpha_{t+1})}{C_{t}(\alpha_{t})}$. Hence, the rates of growth in GDP and the augmented index equate when damages change at the GDP growth rate. The upshot of this result for policymakers is the following. When damages rise more (less) rapidly than GDP, growth estimates based on GDP overestimate (underestimate) comprehensive growth.

b. **Augmented Accounts with Pollution Abatement.**

Next, abatement is added to the model. Growth in (2) between time periods (t) and (t+1) is shown in (5).

$$\frac{Y_{t+1}^{e}-Y_{t}^{e}}{Y_{t}^{e}}=\frac{Y_{t+1}^{m}-Y_{t}^{m}+\left(C_{t}(\gamma_{t})-C_{t+1}(\gamma_{t+1})+\left(C_{t}(\alpha_{t}-\beta_{t}\gamma_{t})-C_{t+1}(\alpha_{t+1}-\beta_{t+1}\gamma_{t+1})\right)\right)}{Y_{t}^{e}} \tag{5}$$

This expression reflects two facets of growth in an extending national accounting identity previously reported in the literature. First, there is a positive effect on growth when expenditures on abatement and damages fall through time (Le Kama and Schubert, 2007; Hoel and Sterner, 2007; Heal, 2009; Gollier, 2010; Baumgartner et al., 2014; Six and Wirl, 2015; Muller, 2019). Second, the net effect on growth of including abatement expenditure and damages from current period consumption depends on both the trajectories and relative magnitudes of abatement and damage (Muller, 2019). If both are increasing, growth is diminished. If both are falling, growth is enhanced. If, say, damage falls when abatement expenditures rise, then the impact on growth depends on which is larger.

Next, (5) is compared to growth in the market index.

$$\frac{Y_{t+1}^{e}-Y_{t}^{e}}{Y_{t}^{e}}-\frac{Y_{t+1}^{m}-Y_{t}^{m}}{Y_{t}^{m}}=\frac{C_t\Delta_t Y_{t+1}^{m}}{Y_t^e Y_t^m}-\frac{C_{t+1}\Delta_{t+1}}{Y_t^e} \quad (6)$$

where: $\Delta_t = (\alpha_t - \beta_t\gamma_t + \gamma_t)$, and $\Delta_{t+1} = \alpha_{t+1} - \beta_{t+1}\gamma_{t+1} + \gamma_{t+1}$. This expression is equivalent to (4) except that (6) includes both damage and abatement.

With pollution abatement, under what conditions do the growth rates in market output and augmented output coincide? Setting (6) equal to zero and rearranging yields:

$$\frac{Y_{t+1}^{m}}{Y_{t}^{m}}=\frac{C_{t+1}\Delta_{t+1}}{C_t\Delta_t} \quad (7)$$

This indicates that when growth in the monetary expenditure on abatement plus damage equals the GDP growth rate, the two indices change at the same rate. Alternatively, when the combined drag from abatement and damage change at the same rate as GDP, the expansion (or contraction) of the augmented measure of income and GDP align. To see this more clearly, suppose growth in the money value of abatement and damage exceeds the rate of growth in GDP by some small amount (ε). Adding (ε) to the left-hand side of (6) and re-arranging yields: $C_{t+1}\Delta_{t+1} = C_t\Delta_t\left(\frac{Y_{t+1}^{m}}{Y_t^m}+\varepsilon\right)$. Then, evaluating (5) results in: $\frac{-\varepsilon\Delta_t C_t}{(Y_t^e)}$. Thus, incrementally higher growth in abatement and damage exerts a negative effect on the difference in growth rates between the augmented indicator and GDP.

What does one learn from the above exercises? Policymakers charged with assessing economic performance will mischaracterize growth by ignoring damages and abatement. In a pre-policy economy, errors in growth accounting depend strictly on damage. The sign of the mistake depends on the sign of the change in damage. The magnitude of the error also depends on the initial period pollution intensity. Once an economy adopts environmental policy, the trajectories of abatement and damage together determine whether market-oriented growth estimates differ from comprehensive estimates and how.

III. Methods.

This section begins with the mechanics of the exposure, mortality, and damage calculation. Using population by age cohort (a), state (i), and time (t), denoted ($Pop_{a,i,t}$), and baseline (reported) mortality rates, by (a), (i), and (t), denoted ($M_{a,i,t}$), (CDC, various) premature mortality due to $PM_{2.5}$ exposure is computed as shown in (8).

$$Mort_{a,i,t} = Pop_{a,i,t} M_{a,i,t} \left(1 - {}^{1}\!/_{exp\left(\theta PM_{i,t}\right)}\right) \quad (8)$$

The (θ) term is reported in the empirical evidence reported in the epidemiological literature (Krewski et al., 2009). Recent work in environmental economics explores the exposure-mortality relationship using causal models (Jha, Muller, 2019; Deryugina et al., 2016; Ebenstein et al., 2017). Papers that have explored exposure to annual mean levels in an instrumental variables context (Jha and Muller, 2019) report estimates of (θ) that are in line with the values from the epidemiological literature. It is difficult to directly compare results from other recent studies that estimate the effects of daily exposure on daily mortality rates (Deryugina et al., 2016). In addition, other studies apply quasi-experimental methods in very different contexts, rendering meaningful comparisons difficult (Ebenstein et al., 2017).

Aggregating over age groups and locations yields an estimate of national premature mortality. Monetary damages (*D*) are calculated by simply multiplying premature mortalities times the VSL.

$$D_t = Mort_t V_t \tag{9}$$

Note that the VSL (V_t) varies by year according to the reported per capita income and estimates of the VSL-income elasticity reported in the literature (Kleckner and Neumann, 1999; Costa, Kahn, 2004; Hammitt, Robinson, 2011). Hammitt and Robinson (2011) provide evidence that the VSL-income elasticity itself varies according to income. In particular, studies focusing on higher income countries in the modern era tend to report lower VSL-income elasticities. In contrast, analyses probing developing economies, or historical time-periods in what are now developed economies find higher elasticities. In light of this, the present analysis employs the decadal VSLs reported in Costa and Kahn (2004) for mortality risk valuations from 1957 to 1980 (which imply a variable income elasticity). For the 1980 to 2016 period, the paper uses the USEPA's recommended VSL of $7.4 million ($2006). This value is adjusted for real income using the USEPA's 0.4 income elasticity. VSLs implied by the two different approaches used herein equate in 1980. Figure A.3 in the appendix shows how the VSL from 1957 to 2016.

Expression (10) demonstrates how VSLs in different time periods are calculated with respect to a base period VSL (V_0). In time period (t), (V_t) is:

$$V_t = V_0 \left(\frac{I_t}{I_0}\right)^{\varepsilon_v} \tag{10}$$

where: I_t = real personal income in period (t)

ε_v = VSL-income elasticity.

For the 1980 to 2016 period, the concentration data used in (8) are spatially resolved satellite, modeled, and monitored "readings" of ambient $PM_{2.5}$. Meng et al., (2019), provide the data in 1° latitude-longitude coordinates by year from 1980 to 2016. The data are geolocated and then averaged to the state level, by year. These estimates are then fed into (8) and to compute state and national damages. Figure A.1 in the appendix demonstrates the close correspondence between the satellite data and USEPA's monitor data over the 1999 to 2016 period for which both datasets are available.

The pre-1980 historical $PM_{2.5}$ data is derived from USEPA monitoring data for total suspended particulates (TSP) provided by Clay et al., (2016). $PM_{2.5}$ is a sub-set of TSP. On this basis, one hypothesis is that TSP yields useful information regarding $PM_{2.5}$ levels, though $PM_{2.5}$ was not separately monitored prior to 1999. As such, a linear regression model is fitted to the overlapping series of $PM_{2.5}$ and TSP monitoring data. (This includes the years 1999 through 2016.) This is shown in (11).

$$PM_{i,t}^{2.5} = \beta_0 + \beta_1 TSP_{i,t} + \beta_2 Year_t + \varphi_i + \varepsilon_{i,t} \qquad (11)$$

The $(\beta_0, \beta_1, \beta_2)$ terms are OLS parameter estimates. The (φ_i) term reflects state fixed effects, and $(\varepsilon_{i,t})$ is a stochastic error term. Then, using the fitted coefficients, a series is extrapolated back through 1957 using national average TSP levels. The results of this fitting and extrapolation exercise are only used from 1980 back to 1957. Further, the series is spliced to the series provided by Meng et al., (2019) to ensure continuity in 1980. Table A.3 in the appendix reports the fitted coefficients from three variants of (11). The first features OLS estimation without state fixed effects. The second includes state fixed effects. The third specification includes state specific linear trends. Adopted is the second specification (with state fixed effects). The entire spliced time series of national, annual average $PM_{2.5}$ levels along with the monitored TSP series is shown in figure A.2. Figure A.2 displays the 95 percent confidence intervals on the predicted $PM_{2.5}$ levels prior to 1980 (since the 1980 forward values are from satellite data there are no standard errors).

a. Integration of the GED into the NIPAs.

The standard approach to augmenting national accounts with pollution damage that manifests outside of (or external to) markets is to deduct such impacts expressed in monetary terms from an aggregate measure of output such as GDP or Value-Added (VA) (Abraham and Mackie, 2006). GED is subtracted from national GDP to estimate environmentally adjusted VA (EVA). The analysis then computes growth in both GDP and the EVA.

State-level GED are debited from PCE. Ambient pollution levels in a location are an amalgamation of discharges from many sources. Hence, subtracting exposure-based GED from GDP produced in a particular state would potentially "charge" that state with impacts from emissions produced elsewhere. In recognition of the asymmetry between geographically resolved measures of production and exposure to pollution, the state GED is deducted from PCE to estimate environmentally adjusted PCE or EPCE.

The USBEA reports PCE nationally from 1980 – 2016, and by state from 1997 forward (USBEA, 2018). State GDP is reported over the full 1980 – 2016 time series. State PCE from 1996 back to 1980 is imputed using the state specific ratio of GDP to PCE from 1997 forward.

b. Descriptive Regressions on Determinants of Growth and Damage.

In order to characterize how various relevant factors affect the GED and EPCE growth rates, the empirical analysis includes a set of descriptive regression exercises. The models regress the GED growth rates (by state) and the spread between the EPCE growth and GDP growth (at the state-year level) on three groups of covariates. These include a set of macroeconomic controls: the federal funds target rate (FRED, 2018), state-level unemployment rates (BLS, 2016), housing starts (Census, 2018), an indicator for years including an NBER recession, and state level population (CDC Wonder, 2018). The next group of covariates features state level (per capita) fossil fuel and electricity consumption delineated according to fuel type (petroleum, natural gas, and coal). These variables are further decomposed according to sector of end use: electric power generation, transportation, industrial, commercial, and residential (USDOE SEDS, 2018). The third collection of regressors model environmental policy. This group includes indicators for the two phases of the Acid Rain Program (interacted with coal and natural gas-fired electricity consumption), indicators for years in which the $PM_{2.5}$ or the O_3 NAAQS were tightened, counts of counties (within each state) out of attainment with the NAAQS, an indicator for states having a renewable portfolio standard (RPS), and whether states featured deregulated electricity markets. The models also feature state and year fixed effects. Of particular interest are the controls for environmental policies and their association with both damages and EPCE growth spreads over PCE growth. Importantly, the analysis does not claim to identify causal policy effects. Rather, the models are intended to provide provocative results interpreted as associations between the covariates and the outcome variables. Quasi-experimental designs intended to tease out causal policy effects are left to future work.

IV. Results.

The results section proceeds in three parts. The first sub-section gives an account of mortality and the national GED estimates from 1957 to 2016. The second sub-section details the GED and EVA (again in both levels and growth rates) back to 1980. And, the third part discusses the fitted coefficients from the descriptive regression analyses.

a. Deaths and Pollution Damage Intensity: 1957 - 2016.

Figure 1 plots the number of $PM_{2.5}$ induced deaths nationwide from 1957 to 2016. In 1957, about 430,000 deaths were estimated to be associated with $PM_{2.5}$ exposure. This is roughly four-times more deaths from $PM_{2.5}$ than calculated for 2016. The CDC reports that about 1.7 million deaths occurred in 1957. Thus, $PM_{2.5}$ associated deaths amounted to about one-quarter of all mortalities. In an attempt to bound this figure, recent estimates of $PM_{2.5}$ associated mortalities in China are compared to the 1957 death estimate for the U.S. Specifically, Rohde and Muller (2015) report that in 2014, 1.6 million deaths occurred due to exposure to $PM_{2.5}$. This amounted to 17 percent of all deaths. Hence, the mortality burden from $PM_{2.5}$ in the 1950s in the U.S. was quite similar to that in China in very recent years. How did the $PM_{2.5}$ levels compare? The annual average $PM_{2.5}$ level reported in the Rohde and Muller (2015) study was 52 ug/m^3 while that in the U.S. in 1957 was 54 ug/m^3. An important contributing factor to the difference in the $PM_{2.5}$ mortality burden between the U.S. in 1957 and China in 2014 is that the baseline (population-weighted) mortality rate in the U.S. in 1957 was about 9.9/1000 whereas that for China in 2014 was 7.2/1000.

Figure 1 indicates that deaths from $PM_{2.5}$ fell to around 400,000 by 1960, and then, with some oscillation, dropped to about 350,000 in 1970. Between 1970 and 1980, deaths from $PM_{2.5}$ fell to

250,000. Importantly, 1970 saw the passage of the Clean Air Act. Further, the energy crisis and associated recession from 1973 to 1975 was concurrent with a significant reduction in deaths. The sharp recessions from 1980 to 1982 reduced air pollution mortality to close to 200,000. From 1982 onward, mortalities then roughly linearly decreased to just over 118,000 in 2016. The CDC reports that 2.7 million deaths occurred in 2016. Hence, $PM_{2.5}$-associated deaths accounted for just about four percent of all mortalities in 2016.

Several broad or national level, trends affect the change in deaths from particulate air pollution. First, from 1957 to 2016, the estimated annual average $PM_{2.5}$ level dropped by a factor of seven[4]. Additionally, the population-weighted average mortality rate declined from 9.6 per 1,000 to 8.5 per 1,000 (CDC, 1959; CDC, 2018). Countervailing the dramatic reduction in $PM_{2.5}$ and the reduction in mortality rates was population growth. In 1957, the U.S. population was about 172 million, whereas in 2016 the U.S. had grown to 323 million.

In addition to the broad changes driving the reductions in deaths, more subtle forces were also at work. Note, as shown in (8) that deaths from exposure are multiplicatively related to baseline mortality rates. As such, differences in the distribution of (within-year) baseline mortality rates are a potentially important driver of both the level and the distribution of damages. Figure A.4 reports the share of total $PM_{2.5}$ induced deaths among populations over 65 years of age. The share of deaths among the elderly increased from 60 percent in 1957 to over 75 percent in the late 1990s. Figure A.5 indicates that this mapped closely to the aging of the U.S. population. However, after the year 2000, the population continued to age, but the share of $PM_{2.5}$ deaths among the elderly fell slightly through 2016. There are likely two explanations for this pattern.

[4] Yet, deaths from $PM_{2.5}$ fell by a factor of four. This less-than-proportional response ultimately derives from the mortality dose-response function used herein (Krewski et al., 2009).

First, abatement of $PM_{2.5}$ occurred in places consisting of relatively older populations (such as the industrial Midwest). Second, relative growth in the population over 65 tended to occur in lower $PM_{2.5}$ locations: the western U.S. for example.

Figure 2 reports the GED-to-GDP ratios from 1957 to 2016. From 1957 to 1960, pollution intensity fell from 30 percent of output to about 27 percent. Then, during the 1960s, GED-to-GDP increased to nearly 40 percent. The peak pollution intensity occurred in 1971, one year after passage of the Clean Air Act. There was then a remarkably steep decline in pollution intensity until 1980 when GED comprised about 25 percent of GDP. The GED-to-GDP ratio declined from 0.25 in 1980 down to under 0.10 in 2016.

Figure 2 also includes a plot of the annual average $PM_{2.5}$ level. Beginning in the late 1950s, $PM_{2.5}$ averaged about 55 ug/m^3. Ambient concentrations fell rapidly to about 40 ug/m^3 by the mid-1960s. (The steep drop in monitored, ambient TSP corroborates this estimated reduction over this time period shown in figure A.2.) In 1980, $PM_{2.5}$ averaged about 25 ug/m^3. $PM_{2.5}$ levels fell steadily through the 1980s and essentially through the rest of the decades covered herein.

Figure 2 also reveals that from 1970 to the early 2000s, GED/GDP fell more rapidly than pollution levels. This implies that either pollution fell in high damage locations (like large cities), or that GDP growth outpaced pollution and damage reductions, or a combination of the two factors. Both the 1980 through 1982 recessions and the Great Recession were associated with sharp reductions in GED. Following the year 2000, pollution intensity and ambient $PM_{2.5}$ declined in lock step.

b. Comparative Growth Rates in GDP, EVA, and GED: 1957 - 2016.

Table 1 summarizes the annual growth rates in GDP, GED, and EVA by decade. (All growth rates are expressed in per-capita terms.) Over the entire sample, real GDP growth averaged just under two percent; damages fell by an average of 0.41 percent, and EVA expanded by 2.45 percent. Hence, EVA outpaced GDP by about one-half of a percentage point. There was, of course, considerable heterogeneity in this growth rate spread. From 1957 through 1970, GDP grew more rapidly than EVA did. As the conceptual model suggested, accounting for pollution damage attenuates growth when pollution intensity rises. From 1957 to 1970, GED grew by 4 percent, annually.

As pollution levels plummeted through the 1970s, GED fell by 1.06 percent per annum, and EVA exceeded GDP growth by 1.5 percentage points. During the 1980s, real GDP per capita increased by an average of 2.2 percent while EVA grew by 3.2 percent. GED declined by about 1.4 percent, per year. During this decade, the EVA indicator suggests the American economy grew by one full percentage points more rapidly than GDP. During the 1990s, the spread between EVA and GDP growth fell to 0.70 percent. The rate of GED reduction accelerated to about 1.75 percent. The 2000s featured attenuation of both GDP and EVA growth as the economy incurred the effects of the Great Recession. EVA outpaced GDP by 0.5 percentage points. During this decade, GED fell by nearly three full percentage points per year. Although subsequent sections of this analysis delve more deeply into factors associated with changes in the GED, it is helpful to note at this point that this decade featured the implementation of Phase II of the Acid Rain Program, several reductions in the NAAQS, and the significant substitution from coal to gas in power production. Finally, during the 2010s, the rate differential contracted to under 0.2 percentage points. Table A.1 in the appendix repeats this exercise using the alternative VSL assumptions. The patterns are essentially robust to the different VSL assumptions.

Table 2 summarizes growth rates according to the business cycle. During recession years, annual GDP growth was -0.32 percent on average, whereas EVA growth was 0.39. This is a difference of 0.7 percentage points. Note that the GED, on average, contracted by 3 percent during recession years. In contrast, when the U.S. economy was not in recession, EVA outpaced GDP by about 0.4 percentage points. (GED tended to increase slightly during expansionary periods.) Hence, whether the economy is in recession or not explains about half of the difference between EVA and GDP growth over all six decades. It is also interesting to note that the sign of GED growth hinges on whether the economy is in recession or expansion – irrespective of regulatory constraints.

Table 2 reports growth summaries for two major macroeconomic shocks: the energy crisis of the 1970s and the Great Recession. During the energy crisis years of 1973 through 1975, GDP growth was positive but below the sample average. EVA growth, by contrast was nearly 4 percent – significantly above the average of 2.45 percent. The growth rate differential between EVA and GDP during the energy crisis was 2.20. Further, pollution damage fell abruptly by nearly 3 percent, annually. During the Great Recession, GDP growth was -1.19, EVA contracted by 0.73 percentage points and GED fell precipitously at over 5 percent. (Table A.2 in the appendix repeats this analysis using the alternative VSL assumptions.)

Figure 3 presents indexed values of per-capita GDP (solid line), the EVA (dashed line) and GED (dashed-dotted line) from 1957 to 2016. (This figure employs the default, time variant VSL-income elasticity.) First, the GDP index reveals the remarkable growth that has occurred within the market economy since 1957. In real terms, the U.S. economy has grown by nearly three times in this 60-year period. The shaded areas represent recessions. The early 1980s recessions and the Great Recession had a large effect on GDP growth. Both the 1990 recession and the downturn associated with the bursting of the "tech bubble" had mild effects on growth.

The dashed line represents EVA growth. Accounting for air pollution damage suggests that the U.S. economy has more than tripled in size since 1957. Dividing figure 3 into two time-periods (before and after the energy crisis of 1973 to 1975) is useful. Prior to 1973, GDP growth exceeded EVA growth because GED grew more rapidly than GDP. Figure 3 shows that GED increased by nearly 50 percent during the 1960s. GED then plateaued in 1970. From the beginning of the energy crisis onwards, real GED per capita fell. Once GED began to fall, the EVA index caught up to GDP and then for the remainder of the sample period, EVA growth outpaced GDP (corroborating the results in table 1).

Two factors explain these macroeconomic patterns, both of which were elucidated by the conceptual model above. First, the U.S. economy, as measured by the EVA index was about 30 percent smaller around the time of the energy crisis than GDP would suggest. Thus, growth in EVA occurs over a smaller base than GDP. Second, pollution damage fell from 1973 to 2016. The conceptual model highlights that these two effects increase the differential between EVA and GDP growth. Figure 3 provides an illustration of how these factors affect the relative growth rates of EVA and GDP in the U.S. economy.

c. State Growth: 1980 to 2016.

Do the comparisons between adjusted output and the market indices at the state level resemble the national scale results? Importantly, when analyzing states, the focus shifts from GDP to personal consumption expenditures (PCE) because of the difficulty attributing damages, exposures, and concentrations in a given state to the location of emissions. As such, the adjusted index (EPCE) features the deduction of the GED from PCE in a given state-year.

Figure A.7 in the appendix plots the growth indices for four state economies: Pennsylvania, West Virginia, Texas, and North Dakota. The top-left panel shows that the Pennsylvania economy (as measured by PCE) just about doubled between 1980 and 2016. When measured by EPCE, this state economy expanded by six times. Concomitantly, GED fell by one half. The factors that contributed to the U.S. EVA growing more rapidly than GDP are at work here as well. In the base year, GED comprised nearly 50 percent of Pennsylvania PCE. The pollution intensity of output in Pennsylvania plummeted to just 11 percent in 2016. Not only did the state begin with a heavy burden of pollution damage, but also the Pennsylvania economy cleaned-up significantly. Both effects, as explicated by the conceptual model, contribute to the dramatically faster growth in EPCE relative to PCE.

The top-right panel of figure A.7 displays the growth indices for West Virginia. Real PCE grew such that the 2016 economy was about twice the size of the 1980 economy. EPCE growth, however, was much higher. The EVA index suggests West Virginia's economy expanded by almost seven times. Damages dropped by about one-quarter. Like the case Pennsylvania, the stark difference in economic performance suggested by the EPCE and PCE indices in West Virginia stems from substantial reductions in pollution intensity: from about 50 percent down to under 20 percent between 1980 and 2016. As this state's economy mitigated the burden of air pollution exposure and health risks, it grew far more rapidly. The value of these risk reductions is not captured by PCE.

Pennsylvania and West Virginia are likely integrated and share aspects of the composition of their economies. An economy such as Texas presents a different case, both in terms of composition and region. The bottom-left panel of figure A.7 displays the growth indices for Texas. The first pattern evinced in the figure is the much smaller disparity between EPCE and PCE than either Pennsylvania or West Virginia. Why does this occur? Texas never had the grossly high GED/PCE metrics registered in Pennsylvania and West Virginia. In 1980, the GED/PCE index in Texas was about 0.15. It subsequently fell to 0.06 in 2016.

The bottom-right panel of figure A.7 repeats this exercise for the North Dakota state economy. Like Texas, the difference between EPCE and PCE is modest throughout the 1980 – 2016 time period. Further, real PCE and EPCE fell from 1980 until the late 1990s. From that time forward, PCE increased in real terms. And, as GED remained lower than the 1980 level, EPCE began to outpace PCE growth. Additionally, figure A.7 detects the oil and gas extraction boom in these aggregate statistics. The rapid rise in both PCE and EPCE in 2011 coincides with the increase in extraction in North Dakota's Bakken Formation.

d. Descriptive Regressions.

Tables 3 and 4 report the results from the descriptive regression analyses. For each model, the unit of observation is the state-year. The thrust of these empirical exercises is to provide a sense of how three sets of factors affect the GED and EPCE growth rates: macroeconomic factors, energy consumption, and environmental policies. Importantly, tables 3 and 4 only present results for those covariates that display significant relationships to the dependent variables. Table 3 begins with the regressions of GED growth rates. Whether or not the economy is in recession has a large and robustly significant effect on GED growth ($p < 0.01$). In column (1), the model only includes state fixed effects. In this context, being in a recession year deducts two percentage points from the GED growth rate. However, upon inclusion of year fixed effects (column 2), the effect of a recession rises considerably; being in a recession year is associated with a 25 percentage point reduction in GED growth. The top income tax rate is negatively associated with damage growth. Unemployment rates, housing starts, and population do not exhibit robust or significant influences on the GED growth rate.

Table 3 also includes the controls intended to characterize how environmental policy affected the GED. Specifically, table 3 includes contemporaneous measures and up to two year lags of years when the NAAQS for $PM_{2.5}$ and O_3 were tightened. When controlling for year fixed effects, the two-year lag measure of the $PM_{2.5}$ NAAQS is significantly associated with a reduction in GED growth ($p < 0.01$). The association is also economically significant: about a nine-percentage point reduction in GED growth. Further, the concurrent measure of O_3 NAAQS changes exhibits a significant, negative effect on the GED ($p < 0.01$). Although the GED encompasses $PM_{2.5}$, emissions of precursors to O_3 production (NO_x and VOCs) also affect $PM_{2.5}$ levels. As such, it is plausible that O_3 NAAQS adjustments affect $PM_{2.5}$ exposures.

Table 4 covers the regressions with the growth rate differential between EPCE and PCE as the dependent variables[5]. Table 4 begins with macroeconomic controls. Whether or not the economy is in recession has a significant effect on the rate spread. Specifically, controlling for state and year fixed effects, recession years feature rate spreads that are about five percentage points greater than non-recession years ($p < 0.01$). Recall that table 3 reported a large, negative, and

[5] The EPCE-PCE differential is used since these are state level regressions.

significant effect of recessions on damages. Since EPCE rises when GED falls, this result supports that in table 3.

The federal funds rate also exhibits a significant association with the EPCE-PCE rate differential. Without year fixed effects, the federal funds rate is positively associated with the rate spread ($p < 0.01$). Inclusion of year fixed effects reverses the sign ($p < 0.01$). The interaction term between the federal funds rate and the recession indicator is robustly significant and positively associated with the EPCE - PCE growth rate spread.

The income tax rate on the highest income bracket is strongly associated ($p < 0.01$) with higher rate spreads. Recall that table 3 reported a significant negative relationship between damages and the top tax rate. Income taxes tend to dampen consumption. Consumption yields pollution. Hence, as tax rates rise, damages fall increasing the differential between EPCE and PCE growth rates.

While higher levels of housing starts suggest faster market index growth (and lower spreads), table 4 reports evidence of a positive association between spreads and housing starts ($p < 0.05$, inclusive of year fixed effects). One explanation for this is that housing starts have grown more rapidly in the West and Southeast where pollution damages tend to be lower than in the industrial Northeast and Midwest.

Table 4 also demonstrates that greater levels of per-capita petroleum use through transportation significantly attenuates the EPCE-PCE spread ($p < 0.01$). The magnitude of this effect, presumably due to emissions from combustion of gasoline, diesel, and oil, is between one and three percentage points.

Table 4 also explores the links between environmental policy and the EPCE-PCE growth rate differentials. The findings are largely supportive of those reported for the GED in table 3. For instance, two years after the $PM_{2.5}$ NAAQS change, the rate spread is higher by up to four percentage points. And, a similar effect is observed concurrent to O_3 NAAQS amendments: damages fall and the EPCE-GDP differential widens.

V. Conclusions.

This paper conducts the first long run environmental accounting exercise. The analysis focuses on air pollution both because of rich data availability and in light of the fact that this setting has the potential to appreciably affect estimates of both levels and growth in national output. Damage from exposure to fine particulate matter are estimated from 1957 to 2016.

The paper uses standard damage function methods to translate pollution concentrations and exposures into damage. The article reports dramatic levels of pollution intensity in the American economy in years past. In 1957, the paper reports about 435,000 premature mortalities from $PM_{2.5}$ exposure. The mortality burden implied by this estimate is commensurate with the current mortality impacts from $PM_{2.5}$ in China, where ambient levels are approximately on par with the U.S. in 1957. The GED in 1957 comprised between 30 percent and 40 percent of GDP. Damage intensity of output fell precipitously to about 20 to 30 percent of GDP in 1980. Since 1980, the GED/GDP fell to under 10 percent. This reduction was especially rapid prior to 2000, with GED/GDP declining more rapidly than ambient $PM_{2.5}$.

The implication of this stunning clean-up has been rapid growth in EVA, defined as GDP less air pollution damage. Prior to the landmark environmental legislation passed in the early 1970s, GDP grew more rapidly than EVA, as damage intensity in the U.S. economy increased. Since then, EVA outpaced GDP growth as GED declined both in levels and relative to GDP.

It is important to note that applying the VSL-income elasticity and epidemiological results to the damage calculations back to the 1950s and 1960s imparts significant uncertainties into the calculations. Nonetheless, the upshot of these computations is the following: using GDP as the barometer to gauge growth, the U.S. economy has slightly more than double in size since 1957. When EVA (which deducts air pollution damage) is used, the economy has more than tripled in size from 1957 to 2016.

Macroeconomic conditions play a clear role in the differential growth rates. The spread between EVA and GDP growth is 0.3 percentage points higher during recessions than during expansions. During the Great Recession, GED fell by 5 percent annually. Similarly, during the energy crisis of the 1970s, GED dropped by between 2 and 3 percentage points.

The paper also provides evidence of a relationship between tax policy and monetary policy and environmental outcomes. Top tax rates are significantly associated with reduced damages and higher rates of EVA growth, relative to GDP growth. While in depth study of the mechanism is relegated to future work, the connection appears to work through reduced consumption associated with higher rates. In the preferred specification, the federal funds rate, during recessions, is negatively associated with EVA growth, relative to GDP growth.

Regression analysis reveals that the Clean Air Act also played an important role in damage reduction and EVA growth. Detected herein is an effect of NAAQS adjustments on GED and EVA growth. Specifically, years during which (and following) the $PM_{2.5}$ and the O_3 NAAQS were tightened reduced GED, and provided a boost to EVA. Many of the rules governing vehicles and fuel content are difficult to assess because of their overlapping implementation. For instance, controlling for state and year fixed effects the analysis finds little effect of policies like the Acid Rain Program. Additional research is needed to causally parse the effects of the myriad pollution rules on adjusted growth.

The empirical analyses conducted in this paper should stimulate new research in several areas. First, delving more deeply into the state and regional accounts may reveal insights into the relationship between the composition of regional economic systems, policies shaping such systems, and both GDP and EVA growth. Second, this paper's macro-focus leaves unanswered issues related to the distribution of economic resources. Future papers should examine how measures of adjusted income have changed over this 60-year time period. Third, though this paper provides provocative evidence of a link between macroeconomic policy and GED and the EVA-GDP growth rate differentials, more targeted studies of this nexus are warranted. And, finally, the divergent conclusions drawn from measuring economic performance with either EVA or GDP suggest that official statistical agencies should track a set of satellite accounts inclusive of environmental pollution damages.

Figures

Figure 1: Deaths Associated with $PM_{2.5}$ Exposure from 1957 to 2016.

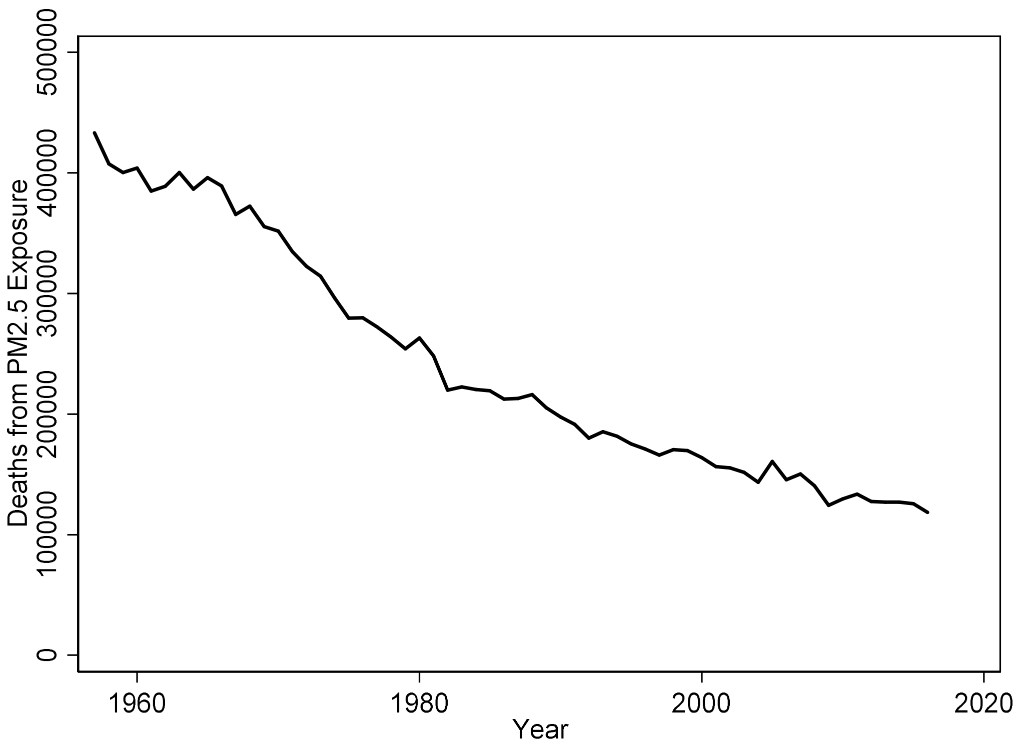
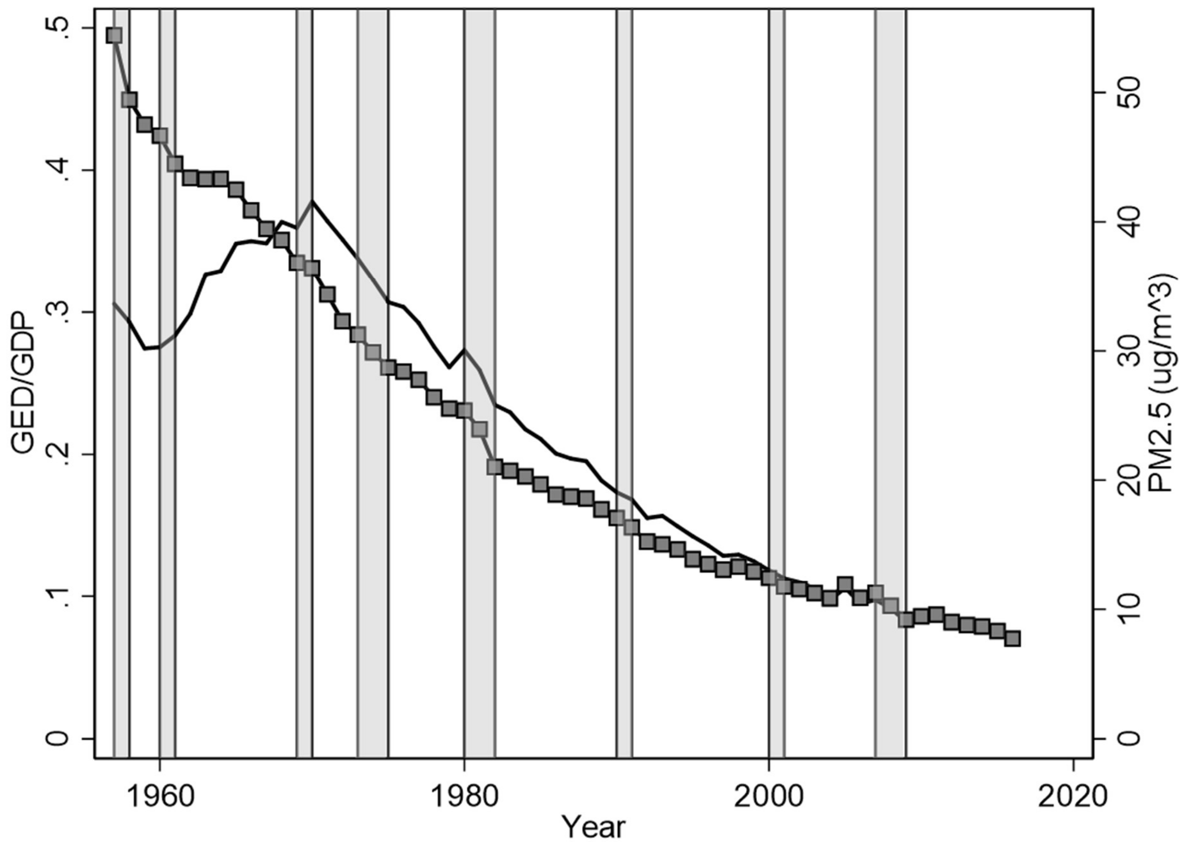


Figure 2: Ambient $PM_{2.5}$ and GED/GDP Ratio for U.S. Economy 1957-2016.

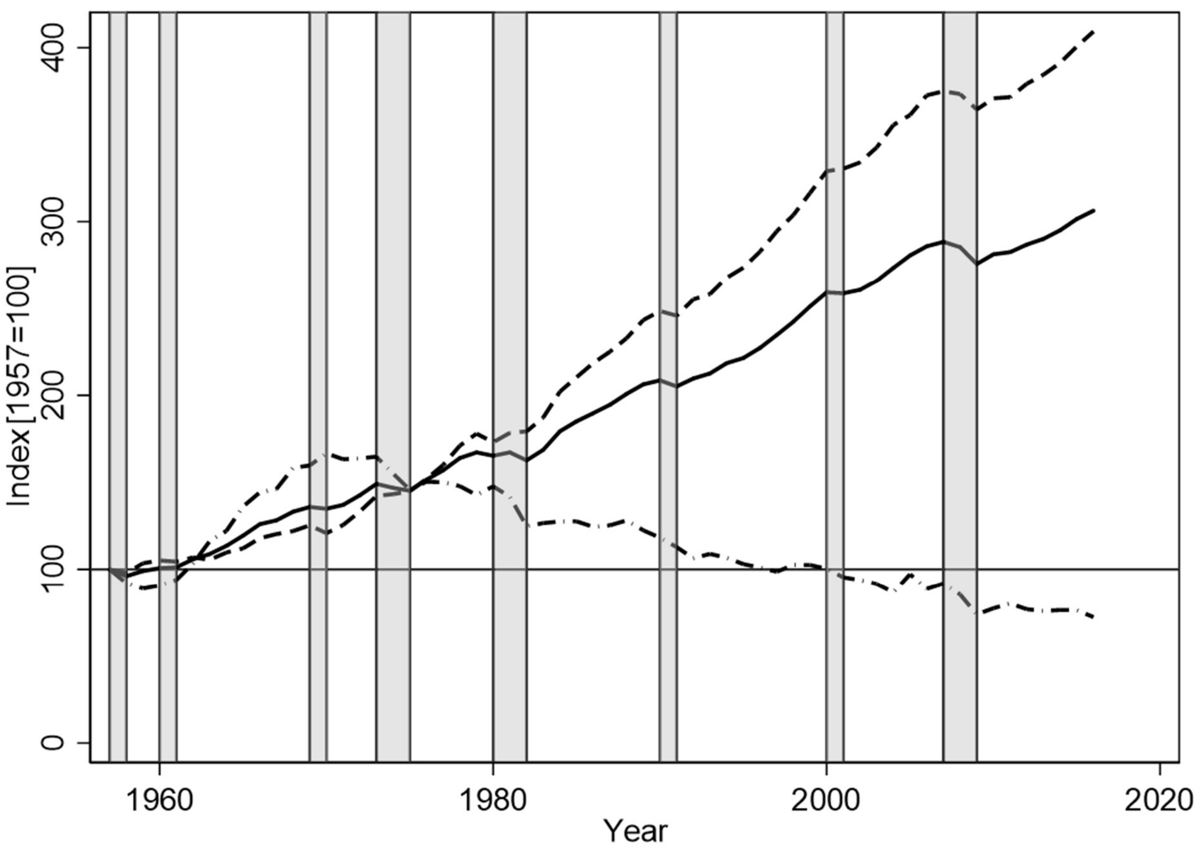


Squares: Ambient $PM_{2.5}$; Line: GED/GDP

GED computed using variable VSL-income elasticity.

Shaded areas demarcate NBER recessions.

Figure 3: Per Capita GDP, EVA, and GED Growth Indices.



Dash = EVA; Solid = GDP; Dash-dot = GED.

GED computed using default VSL-Income Elasticity.

Shaded areas demarcate NBER recessions.

Tables.

Table 1: GED Intensity and Per Capita Growth Rates

in GDP, EVA, and GED.

	Total sample	1960s	1970s	1980s	1990s	2000s	2010s
GDP	1.94[A]	2.62	2.12	2.15	2.00	0.96	1.52
	(2.130)[B]	(2.548)	(2.459)	(2.542)	(1.566)	(2.048)	(0.583)
EVA	2.45	1.93	3.61	3.20	2.68	1.44	1.67
	(2.394)	(2.400)	(3.302)	(2.791)	(1.643)	(1.996)	(0.742)
EVA – GDP	0.51	-0.69	1.49	1.05	0.69	0.48	0.15
	(1.440)	(1.986)	(1.628)	(1.280)	(0.522)	(0.676)	(0.339)
GED	-0.41	4.15	-1.06	-1.42	-1.72	-3.00	-0.24
	(5.335)	(6.067)	(3.444)	(4.518)	(3.016)	(7.018)	(3.698)
GED/GDP	0.21[C]	0.32	0.32	0.22	0.15	0.10	0.08
	(0.100)	(0.0328)	(0.0384)	(0.0294)	(0.0169)	(0.0110)	(0.00476)
N	60	12	10	10	10	10	8

A = average annual growth rate (%).
B = standard deviations in parenthesis.
C = ratio of GED to GDP.
All GED estimates in table 1 employ the default VSL-income elasticity.

Table 2: GED Intensity and Per Capita Growth Rates

in GDP, EVA, and GED and the Business Cycle.

	Time-Variant VSL-Income Elasticity				
	Total sample	Recession	Not Recession	Energy Crisis	Great Recession
GDP	1.94[A]	-0.32	2.85	1.52	-1.19
	(2.130)[B]	(2.134)	(1.289)	(4.318)	(2.151)
EVA	2.45	0.39	3.28	3.72	-0.73
	(2.394)	(2.524)	(1.781)	(4.276)	(1.525)
EVA – GDP	0.51	0.72	0.42	2.20	0.46
	(1.440)	(1.571)	(1.394)	(0.0427)	(0.662)
GED	-0.41	-3.00	0.64	-2.67	-5.65
	(5.335)	(5.516)	(4.947)	(4.576)	(8.568)
GED/GDP	0.21[C]	0.24	0.20	0.33	0.09
	(0.100)	(0.0967)	(0.0994)	(0.0106)	(0.00776)
N	61	18	43	2	3

A = average annual growth rate (%).
B = standard deviations in parenthesis.
C = ratio of GED to GDP.

Table 3: Factors Determining Damage Growth.

	(1)	(2)
Recession	-2.183**	-24.50***
	(1.042)	(2.522)
Federal Funds Rate x Recession	-0.252**	11.73
	(0.102)	(11.33)
Top Income Tax Rate	-0.0201	-2.795***
	(0.0258)	(0.342)
$PM_{2.5}$ NAAQS Change	-3.630***	1.140
	(0.769)	(2.599)
$PM_{2.5}$ NAAQS Change (t - 1)	6.741***	-3.188
	(0.936)	(2.431)
$PM_{2.5}$ NAAQS Change (t – 2)	0.205	-8.940***
	(1.157)	(2.617)
O_3 NAAQS Change	-0.409	-14.85***
	(0.678)	(2.058)
O_3 NAAQS Change (t -1)	-1.043*	-1.693
	(0.585)	(2.739)
O_3 NAAQS Change (t – 2)	-1.457**	-1.101
	(0.605)	(3.199)
State Fixed Effects	Y	Y
Year Fixed Effects	N	Y
adj. R^2	0.145	0.345
N	1554	1554

OLS Standard errors in parentheses

Note: * = $p< 0.1$, ** = $p < 0.05$, *** = $p < 0.01$.

Dependent variable is annual, real GED growth rate.

Table 4: Factors Determining EPCE-PCE Growth Spread.

	(1)	(2)
Federal Funds Rate	0.168***	-12.47***
	(0.0347)	(3.082)
Recession	-1.133***	4.823***
	(0.277)	(0.632)
Federal Funds Rate x Recession	0.301***	11.54***
	(0.0386)	(3.037)
Top Income Tax Rate	0.0552***	1.087***
	(0.0135)	(0.127)
Ln(Housing Starts)	-1.168***	0.844**
	(0.287)	(0.383)
Petroleum Use	-2.236***	-1.756*
Transportation	(0.786)	(0.882)
$PM_{2.5}$ NAAQS Change	1.051***	-0.979*
	(0.173)	(0.569)
$PM_{2.5}$ NAAQS Change (t - 1)	-2.003***	2.948***
	(0.292)	(0.868)
$PM_{2.5}$ NAAQS Change (t – 2)	0.509**	3.942***
	(0.216)	(0.699)
O_3 NAAQS Change	0.140	5.060***
	(0.174)	(0.704)
O_3 NAAQS Change (t -1)	0.649***	-0.887
	(0.155)	(0.643)
O_3 NAAQS Change (t – 2)	-0.338*	-1.521**
	(0.170)	(0.690)
State Fixed Effects	Y	Y
Year Fixed Effects	N	Y
adj. R^2	0.182	0.340
N	1554	1554

OLS Standard errors in parentheses

Note: * = p< 0.1, ** = p < 0.05, *** = p < 0.01.

Dependent variable is annual, real EPCE growth rate less PCE growth rate.

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Supplementary Appendix.

Tables.

Table A.1: GED Intensity and Per Capita Growth Rates in GDP, EVA, and GED.

	Unit VSL-Income Elasticity						
	Total sample	1960s	1970s	1980s	1990s	2000s	2010s
GDP	1.94[A]	2.62	2.12	2.15	2.00	0.96	1.52
	(2.130)[B]	(2.548)	(2.459)	(2.542)	(1.566)	(2.048)	(0.583)
EVA	2.51	3.38	3.27	2.60	2.35	1.41	1.55
	(2.137)	(2.291)	(2.548)	(2.567)	(1.538)	(1.817)	(0.886)
EVA – GDP	0.57	0.77	1.15	0.45	0.35	0.46	0.03
	(1.022)	(1.461)	(0.816)	(1.133)	(0.549)	(0.961)	(0.564)
GED	-0.00	1.12	-1.15	0.43	0.26	-1.83	1.34
	(4.953)	(4.672)	(3.279)	(5.273)	(3.554)	(7.723)	(4.249)
GED/GDP	0.21[C]	0.32	0.25	0.19	0.16	0.13	0.12
	(0.0771)	(0.0164)	(0.0286)	(0.0150)	(0.00868)	(0.0104)	(0.00396)
N	60	12	10	10	10	10	8

A = average annual growth rate (%).
B = standard deviations in parenthesis.
C = ratio of GED to GDP.

Table 2: GED Intensity and Per Capita Growth Rates in GDP, EVA, and GED and the Business Cycle.

	Unit VSL-Income Elasticity				
	Total sample	Recession	Not Recession	Energy Crisis	Great Recession
GDP	1.94[A]	-0.32	2.85	1.52	-1.19
	(2.130)[B]	(2.134)	(1.289)	(4.318)	(2.151)
EVA	2.51	0.58	3.29	2.86	-0.56
	(2.137)	(2.151)	(1.579)	(3.868)	(0.984)
EVA – GDP	0.57	0.90	0.43	1.34	0.63
	(1.022)	(1.215)	(0.914)	(0.450)	(1.194)
GED	-0.00	-3.40	1.38	-2.09	-5.45
	(4.953)	(5.592)	(3.970)	(5.618)	(10.35)
GED/GDP	0.21[C]	0.23	0.19	0.26	0.12
	(0.0771)	(0.0806)	(0.0735)	(0.00870)	(0.0116)
N	61	18	43	2	3

A = average annual growth rate (%).
B = standard deviations in parenthesis.
C = ratio of GED to GDP.

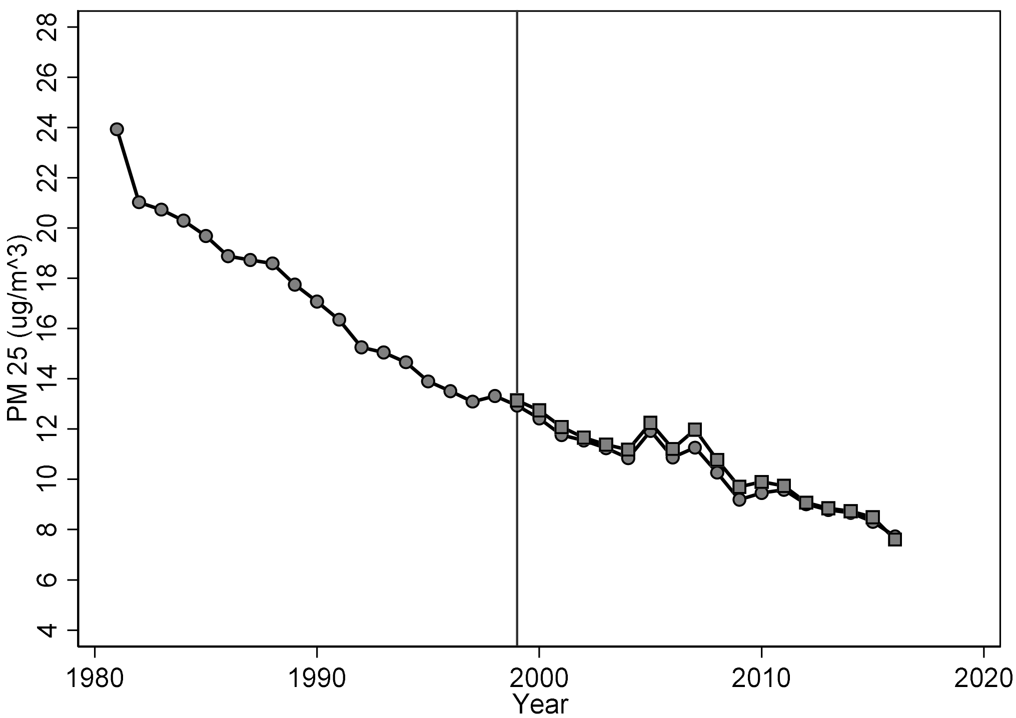
Table A.3: Regression Analysis: $PM_{2.5}$ Prediction Model.

Covariate	(1)	(2)	(3)
TSP	0.049***	0.062***	0.046***
	(0.008)	(0.015)	(0.016)
Year	-0.238***	-0.265***	2.73***
	(0.029)	(0.028)	(0.078)
State Fixed Effects		X	X
State-Year Trends			X
Constant	485.980***	539.819***	234.965***
	(58.358)	(56.487)	(13.055)
N	620	620	620
R^2	0.169	0.169	0.053

se in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Dependent variable is $PM_{2.5}$

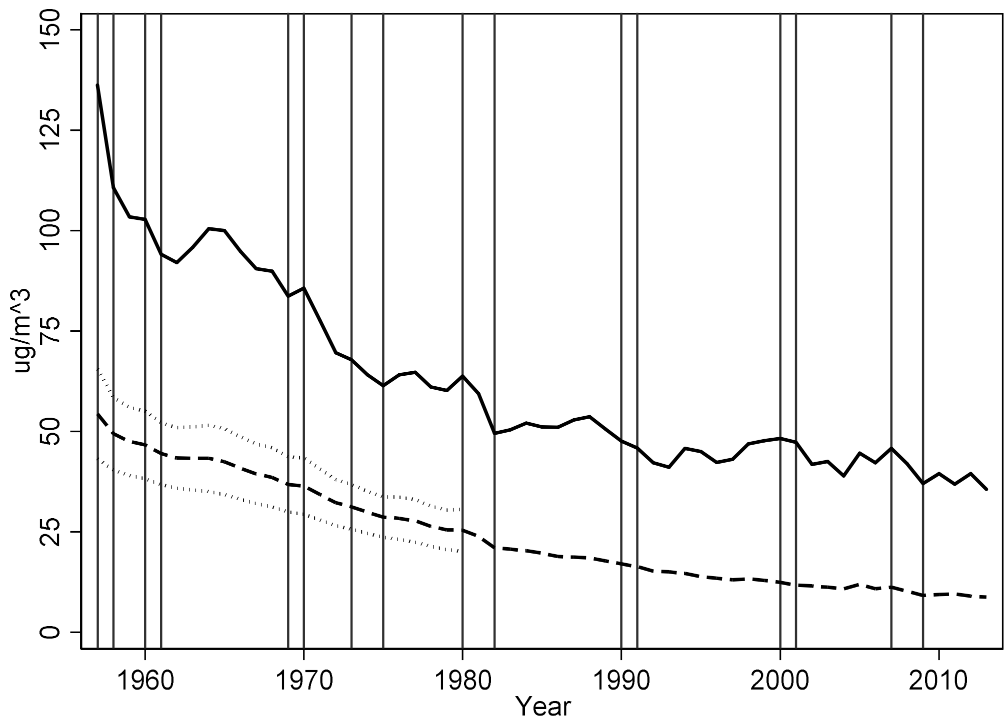
Supplementary Figures.

Figure A.1: Annual Average $PM_{2.5}$ Concentrations: Satellite-Monitor Comparison.



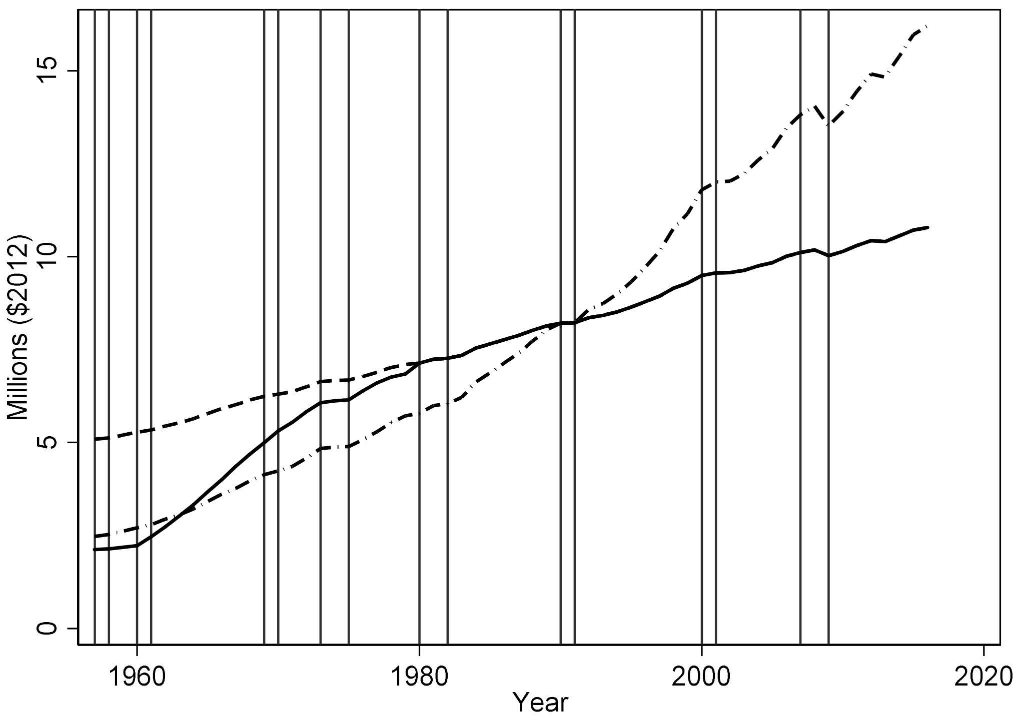
Squares = USEPA AQS Monitor Data, Circles = $PM_{2.5}$ Data from Meng et al., (2019).

Figure A.2: TSP and $PM_{2.5}$ National Average Concentrations.



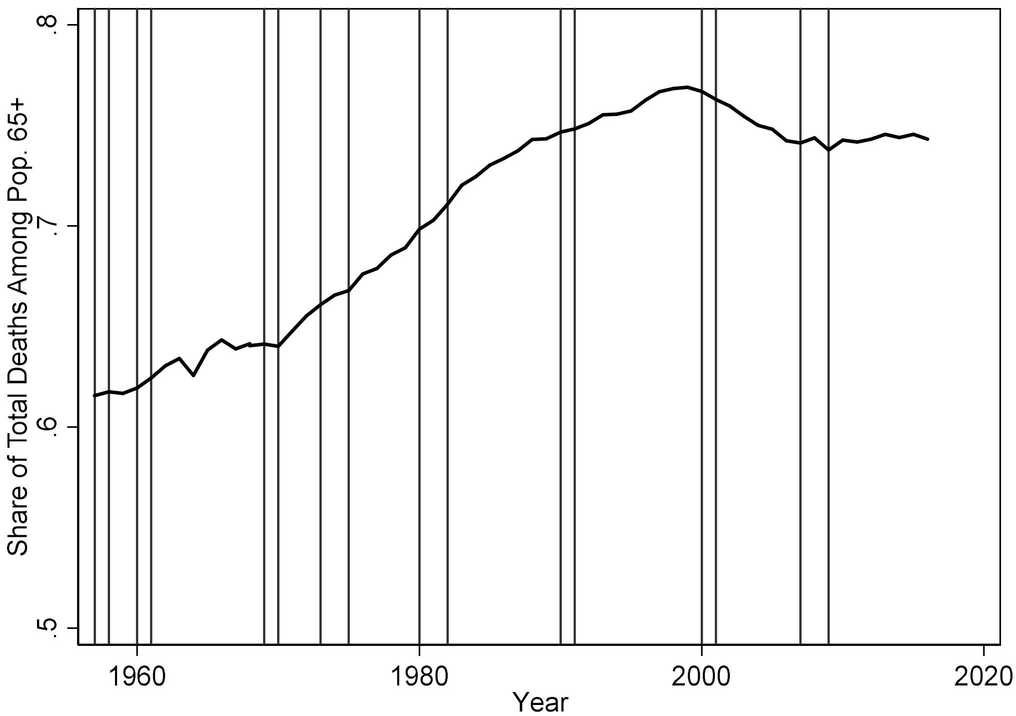
Dash = $PM_{2.5}$ (95% Confidence intervals on predicted values prior to 1980); Solid = TSP
Vertical lines demarcate NBER recessions.

Figure A.3: VSL under various assumptions.



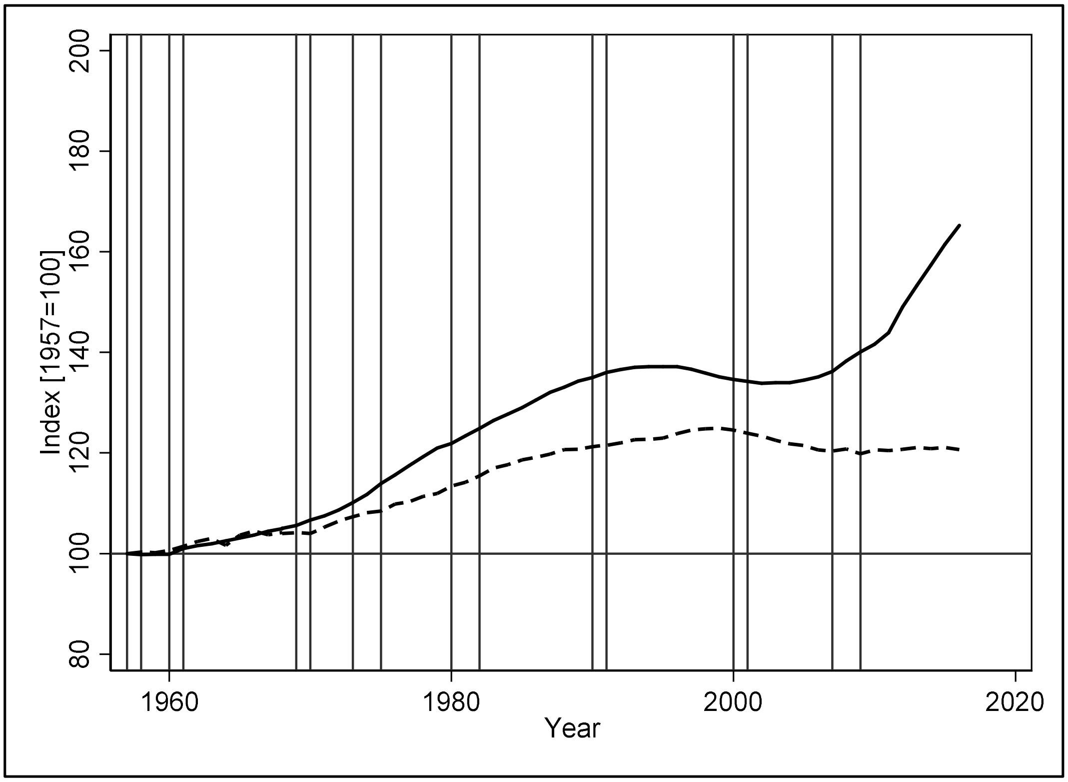
Solid: variable income elasticity; Dash: income elasticity = 0.4; Dash-dot: income elasticity = 1.0.

Figure A.4: Share of All $PM_{2.5}$-Associated Deaths Among Persons Over 65 Years of Age.



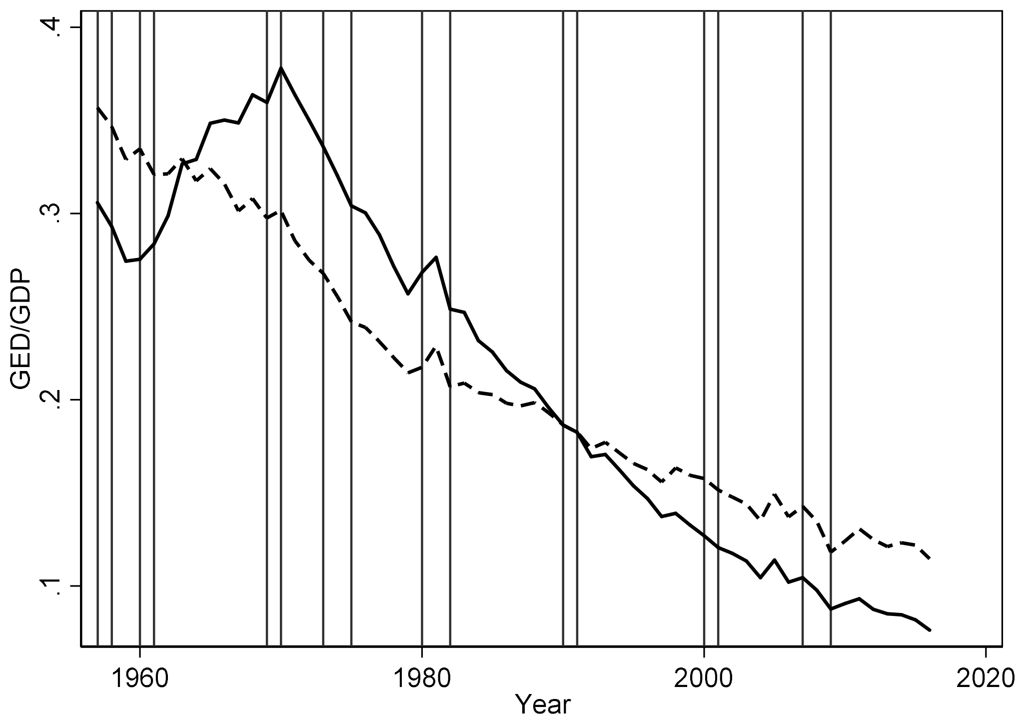
Vertical lines demarcate NBER recessions.

Figure A.5: Indexed Values of Senior Population Share and Senior $PM_{2.5}$ Mortality Share.



Vertical lines demarcate NBER recessions.

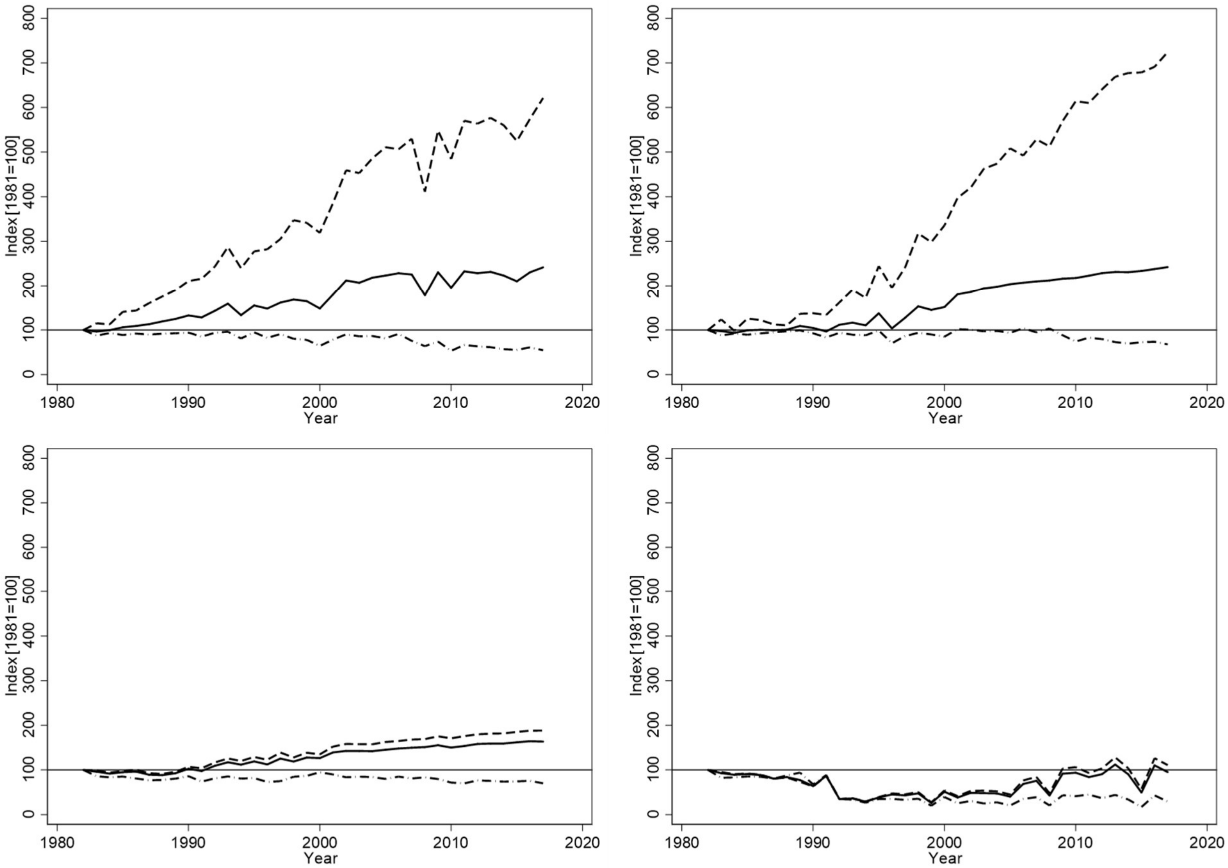
Figure A.6: GED-to-GDP under various VSL–income elasticity assumptions.



Solid: Variable VSL-income elasticity; Dash: Unit VSL-income elasticity.

Vertical lines demarcate NBER recessions.

Figure A.7: EPCE, PCE, and GED in Four State Economies.



Solid = PCE; Dash = EPCE; GED = Dash-dot.
Top-left = Pennsylvania; Top-right = West Virginia; Bottom-left = Texas; Bottom-right = North Dakota.