Environmental Engel Curves

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Abstract

Environmental Engel curves (EECs) describe households' incomes and the pollution necessary to produce the goods and services they consume. We calculate 29 annual EECs from 1984 to 2012 for point-source air pollutants in the US, revealing three clear results. EECs are upward sloping, have income elasticities of less than one, and have shifted down over time. Even without changes to production techniques, pollution would have declined, despite nearly 20 percent growth in real after-tax incomes. This improvement can be attributed about equally to two trends: household income growth represented by movement along inelastic EECs, and economy-wide changes represented by downward shifts in EECs over time.

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Introduction

This paper estimates household-level environmental Engel curves (EECs), which show the relationship between households' incomes and the amount of pollution embodied in the goods and services those households consume. Traditional Engel curves plot relationships between income and consumption of particular goods or services, holding prices constant. They are named for Ernst Engel, a German economist writing in the mid-1800s who studied the degree to which household food expenditures increase with income. Environmental Engel curves describe how households' pollution changes with income. This calculation is less straightforward than for traditional Engel curves, because households generate pollution not only directly as a consequence of their activities such as driving cars, but also indirectly as a consequence of consuming products whose production generates pollution, such as manufacturing the rubber and steel used to make those cars and refining the gasoline used to fuel them. We focus on this larger and less studied component, the indirect pollution generated to produce the goods and services households consume.

Why is this important? Over the past 30 years, total pollution emitted by US producers has declined considerably, even though the real value of US production has increased.[1] Prior research has examined this improvement by parsing the relationship between economic growth and pollution into three components: scale, technique, and composition (Copeland and Taylor, 2005). Scale describes a proportional increase in economic activity—if the economy doubles, the scale effect doubles pollution. Technique describes changes to the pollution intensity of any particular activity, like refining a barrel of petroleum or generating a kilowatt hour of electricity. And composition describes changes to the mix of activities that make up the economy. In the US, pollution due to the growing scale of production has been more than offset by some combination of technique and composition.

Recent research has shown that most of the pollution reductions in the US have resulted from changes in technique. Estimates range from 35 to nearly 100 percent, depending on the pollutant and time period studied.[2] The remaining composition effect itself has two components:

[1] From 1980 to 2012, emissions of carbon monoxide and sulfur dioxide declined by roughly 80 percent, ground-level ozone by 25 percent, and nitrogen dioxide by 60 percent, even though real GDP and real personal consumption expenditures more than doubled (US Environmental Protection Agency, 2014; FRED, 2014a and 2014b).

[2] Levinson (2009) calculates that somewhere between 50 and 95 percent of local air pollution reductions from manufacturing have come from technological change, depending on the pollutant and years examined, with the remainder being due to changes in the composition of output among 450 manufacturing industries. Brunel (2016)

consumption and trade. The US can shift to cleaner products either by *consuming* cleaner goods or—in theory—by importing the relatively pollution intensive goods and exporting the clean ones. But Brunel (2016) and Levinson (2009) both show that changing trade patterns have been small or even in the opposite direction. The composition of US imports has been shifting toward cleaner goods, not more polluting ones, and doing so even faster than the composition of domestic production. That means that the domestic *consumption composition* change towards cleaner goods—the focus of this paper—is larger than the domestic *production composition change* measured by all those prior papers.

We study that consumption composition shift directly, using household consumption data from the Consumer Expenditure Survey (CEX), industry-by-industry emissions factors for five criteria air pollutants from the EPA's National Emissions Inventory (NEI), and input-output tables from the Bureau of Economic Analysis. We use those data to estimate the amount of air pollution required to produce each household's consumption, including all the necessary intermediate goods and services. And from that we calculate EECs separately for each of the five pollutants for every year from 1984 until 2012. With those EECs in hand, we then ask how much of the shift in US consumption toward clean goods comes solely from the fact that the average household today is richer than the average household 30 years ago—a movement *along* an EEC—and how much is due to changes in the mix of goods consumed by all households, holding incomes constant—a *shift* in the EEC.

Some observers have pointed to environmental improvements in the United States and other developed countries as evidence that income growth alone will reduce pollution.[3] But rich countries might have less pollution because they enact strict environmental regulations. The EECs we estimate can help differentiate those sources of cleanup. Economy-wide trends, such as regulation-induced increases in the prices of polluting goods, will appear as downward shifts in EECs. By contrast, an underlying and possibly coincidental preference by richer households for

attributes 35 to 87 percent of the cleanup to technique in the US. For Europe, she shows that the composition of manufacturing has been shifting towards more polluting industries, so the technique changes account for more than 100 percent of pollution reductions. Shapiro and Walker (2015) and Levinson (2015) also credit technique with the vast majority of pollution reductions.

[3] For example, John Tierney wrote in the *New York Times* in 2009 that "the richer everyone gets, the greener the planet will be in the long run" ("Use Energy, Get Rich and Save the Planet," April 20). And Bruce Bartlett wrote in the *Wall Street Journal* in 1994 that "existing environmental regulation, by reducing economic growth, may actually be reducing environmental quality" ("The High Cost of Turning Green," September 14).

cleaner goods will appear as movements along concave EECs. Only the cleanup due to growing incomes along EECs can be considered in any way automatic, without policies or price changes.

One related literature involves so-called “environmental Kuznets curves,” or EKCs, which refer to the aggregate relationship between pollution and national income. Hundreds of published empirical articles in the last 20 years have regressed various measures of pollution on flexible functions of national or regional income.[4] Low-income and high-income regions typically exhibit the least pollution, and middle-income regions the most, resulting in an inverted-U shape or EKC. But EKCs are nothing more than conditional correlations, without meaningful interpretations other than that pollution does not necessarily increase with economic growth. As Grossman and Krueger (1995) recognized in an early such paper “it should be stressed that there is nothing at all inevitable about the relationships that have been observed in the past. These patterns reflected the technological, political, and economic conditions that existed at the time.” Richer countries might have less pollution for any of several reasons. They might enact stricter regulations, use cleaner fuels,[5] have more service-based economies, import relatively more of the most pollution-intensive goods, or—relevant to this exercise—perhaps their citizens choose to consume a less pollution-intensive mix of goods. EKCs cannot tell us why middle-income countries have historically had more pollution than poorer or richer countries.

EECs, on the other hand, are structural, representing income expansion paths holding prices constant. In fact, use of EECs to divide households’ consumption-related pollution changes into two parts yields two of the many possible explanations for the observed inverse-U-shaped EKC patterns of national pollution. Movements along EECs represent changes in peoples’ preferences as their incomes grow, holding prices, technologies, and regulations fixed. And shifts in EECs represent changes in all of those other national characteristics over time.

One approach to estimating EECs would be to compare pollution, income, and consumption choices across countries at a point in time or across time within a country, similar to the way EKCs have been estimated. But EECs based on comparisons across countries or over

[4] For examples in this journal see Harbaugh et al. (2002) and Millimet et al. (2003).
[5] A separate literature on “energy ladders” studies whether richer households choose cleaner fuel types, especially for cooking in developing countries (Hanna and Oliva, 2015). But cooking fuel does not represent an obvious market failure, or externality. Households face the full tradeoff between inexpensive cooking fuel and indoor air quality. We examine whether richer households in the US choose a mix of goods whose upstream production generates less pollution.

time would be difficult to interpret because prices and characteristics of available goods change. Richer countries might pass regulations making pollution-intensive goods costlier or less desirable, causing households to consume proportionally less of them. That difference would not be interpretable as the slope of an Engel curve because it would not represent the change in consumption that results from a ceteris paribus change in income.

Instead, our approach compares pollution, income, and consumption across US households and repeats the analysis separately each year from 1984 to 2012. Households within a given year each face the same relative prices, available products, and environmental regulations.[6] In each year, we combine production-side pollution intensity data with detailed information on household consumption to calculate the total point-source criteria air pollution created as a result of producing the goods and services that each household consumes. Plotting that indirect pollution against those households' incomes yields a set of annual EECs.

We construct these EECs separately for indirect emissions from each of five major air pollutants: particulates, volatile organic compounds, nitrogen oxides, sulfur dioxide, and carbon monoxide. We estimate separate EECs because each is measured in different units and has different environmental consequences. We could imagine other analyses using other datasets that might estimate EECs for other air pollutants, hazardous waste, water pollution, greenhouse gases, or the direct pollution from consumption such as burning gasoline in car engines. In this paper we develop the proof of concept by estimating EECs using these five most commonly studied air pollutants for which the data are most complete.

We also estimate two versions of each EEC: one based solely on income, and one that controls for household characteristics correlated with income: education, age, etc. As the "Engel Curve" entry in *The New Palgrave Dictionary of Economics* notes, "Engel curves may also depend on demographic variables and other consumer characteristics" (Lewbel, 2008). We show that adding those common demographic variables has little effect on the conclusions about the shapes of EECs or how they have changed over time.

Ours is not the first paper to combine household level consumption data with pollution data to generate pollution by income. Metcalf (1999) combines the 1994 CEX with pollution data from 12 industries to study the incidence of a proposed pollution tax. Hassett et al. (2009)

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[6] Prices and regulations do vary across the US, but we can control for that empirically. In some of the parametric analyses that follow we include geography fixed effects, comparing indirect pollution from households with different incomes in the same Census region or state.

combines CEX data from 1987, 1997, and 2003 with pollution data across 50 industries to show that a carbon tax would be increasingly regressive, presumably because EECs are becoming increasingly convex, though they never use that language. And Grainger and Kolstad (2010) and Burtraw et al. (2009) use the CEX to show that a carbon tax would be regressive if not offset by lump sum transfers or reductions in other regressive taxes.

Several papers have studied the relationship between household income and pollution in countries other than the US. Gertler et al. (2016) examine energy use among poor households in Mexico that receive large randomly-timed cash transfers. The randomization addresses concerns about the endogeneity of income and energy use. They find evidence of credit constraints, leading to an s-shaped path of adoption for energy-using appliances, like refrigerators, and nonlinear Engel curves. Allan et al. (2015) use New Zealand Household expenditure data from 2006 and 2012 to show that the income elasticity of indirect greenhouse gasses is less than one and that the EEC shifted down marginally during those 6 years.

No research to date has involved the detailed, year-by-year approach we take. None have the same level of disaggregation as our 850 income and consumption categories and 1000 six-digit NAICS industry classifications. And none maps the results into annual EECs or uses those EECs to decompose changes in US pollution over the past three decades.

We find that EECs display three key characteristics. First, not surprisingly, EECs are upward sloping, meaning that richer households are responsible for more overall pollution. Second, EECs have income elasticities of less than one, indicating that although pollution increases with income, it does so at a rate of less than one-for-one. And third, EECs shift down and become more concave over time, meaning that for any level of real household income, households in more recent years consume a less polluting mix of goods, and pollution increases with income at a decreasing rate. Between 1984 and 2012 real after-tax household incomes in the Consumer Expenditure Survey (CEX) grew by 19 percent, while the various pollutants necessary to produce the goods those households consumed grew at most by one percent and declined by as much as 19 percent.

This reduction in pollution per dollar of expenditures at the household level must come from one of two phenomena: either richer households consume a less pollution-intensive mix of goods holding all else equal—a movement along an inelastic EEC—or households consumed fewer polluting goods in 2012 than did households with the same real incomes in 1984—a downward shift in the EECs. We show that the decline in pollution per dollar was about evenly split between these two effects.

Data and Methods

Estimating EECs requires information on household income and the pollution attributable to each household's consumption. Since we are focusing on indirect pollution, we estimate the amount of pollution that was created in order to produce the specific goods and services consumed by each household in our sample, using information from the Consumer Expenditure Survey (CEX), the EPA National Emissions Inventory (NEI), and the economic and agricultural censuses.[7]

The CEX is collected each quarter by the Census Bureau and provides detailed information on itemized household consumption expenditures.[8] It contains a nationally representative sample of households selected on a rotating panel basis, with roughly 1,500 to 2,000 households entering the survey in any given quarter. Households are tracked for five consecutive quarters, over which they provide information on a wide range of expenditures, income, and other demographics. We group households according to the year and quarter of their second quarterly interview, the first one in which they provide expenditure information. We exclude households with expenditures on nursing homes (0.5 percent of the sample), students, the top and bottom one percent of households based on after-tax income, and any households with incomplete income data. This trimming of the data reduces the sample size from 236,605 to 95,512. To address possible bias that might arise, we reweight the sample based on age groups and homeownership status.[9]

Consumption and income data in the CEX are categorized by approximately 850 separate universal classification codes (UCC) that capture around 80 to 95 percent of total household expenditures. These UCC codes include detailed categories—such as "men's suits" or "wigs, hairpieces, or toupees"—that account for 60 to 70 percent of household spending and broader categories—such as "total purchases at grocery stores"—that account for an additional 20 to 25 percent of spending. The CEX interviews do not collect information on housekeeping supplies,

[7] All of the data are described in detail, along with links to sources, in the online appendix.
[8] The CEX is organized based on "consumer units," rather than "households" (US Bureau of Labor Statistics, 2008). The terms have slightly different definitions, but are often used interchangeably.
[9] We follow the same procedure used by the NBER to create a "usable sample" of CEX extracts with adjusted sample weights (Harris and Sabelhaus, 2000). More details are in the online appendix.

personal care products, or nonprescription drugs, which contribute five to 15 percent of total expenditures (US Bureau of Labor Statistics, 2015).[10]

To calculate the pollution emitted by producing the goods and services associated with those expenditures, we pair the CEX expenditure data with emissions intensities calculated from the NEI.[11] The NEI is a detailed estimate of air pollution emissions in the United States compiled from reports submitted by state, local, and tribal air agencies.[12] The EPA provides summary files that show emissions organized by facilities (point sources, further classified by NAICS industries) or geography (other non-point sources).[13] We calculate the per-dollar emissions intensity of each industry by aggregating industry-level emissions in the 2002 NEI and dividing by the total sales from the 2002 Economic and Agricultural censuses.[14] Since non-point sources of air emissions are not assigned to specific industries in the NEI, our emissions intensities only include pollution associated with specific facilities.

The NEI-based emissions intensities indicate the pollution generated during the production process of each good directly, but we also want to consider pollution from production of the inputs to those goods. For example, if a household purchases a sofa, we would want to know not only the pollution emitted while manufacturing the sofa itself but also the pollution from tanning the leather for its upholstery, milling the wood for its frame, and manufacturing the steel for its springs. Moreover, each of those inputs required its own inputs and pollution. To fully capture the total point-source air pollution associated with each household's consumption, we want to include pollution from manufacturing the products consumed, inputs to those products, and inputs to those inputs ad infinitum up the supply chain.

Upstream pollution from the entire chain of inputs for each item can be estimated using a Leontief (1970) analysis based on the input-output (IO) tables published by the US Bureau of Economic Analysis. These tables show the dollar amount of each input necessary to produce a

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[10] These omitted categories have roughly similar pollution intensities compared to included categories. For example, "soap and cleaning compound manufacturing" falls in the 41st percentile in terms of particulate matter emissions relative to other industries and "pharmaceutical preparation manufacturing" falls in the 22nd percentile.

[11] A prior working paper version (Levinson and O'Brien, 2015) used the Trade and Environmental Assessment Model (TEAM) instead of the NEI. TEAM was developed by an EPA contractor (Abt Associates Inc., 2009) from NEI and other sources. While all of the general findings are similar, the levels of pollution using TEAM data in the working paper did not match aggregates, and so this version uses the official NEI data.

[12] See US Environmental Protection Agency (2016) for a detailed description of the National Emissions Inventory.

[13] The North American Industry Classification System (NAICS) classifies roughly 1,000 industries based on similarities in production processes. NEI pollutant emissions summary files can be downloaded from the EPA at https://www.epa.gov/air-emissions-inventories/pollutant-emissions-summary-files-earlier-neis.

[14] We use 2002 because that was the last year in which the NEI and the Census of Manufactures overlap.

dollar's worth of output for every other industry. Using the IO tables, we transform the direct emissions intensity coefficients into total coefficients that include the pollution to manufacture each final product, all of its inputs, the inputs to those inputs, and so on.[15]

We combine the total pollution intensity coefficients with itemized expenditure information in the CEX to estimate the total amount of pollution created in order to produce each of the categories of goods and services consumed by every household in the survey. By calculating the pollution associated with each spending category for an individual household and then adding up pollution for all categories, we estimate the total amount of pollution attributable to the consumption of each individual household. The final result is a sample of 95,512 households organized in quarterly cross-sections and spread across 29 years of data from 1984 to 2012, in which each household has an estimated total pollution associated with its expenditures.[16] Table 1 shows the average per-household values for this indirect pollution, income, and other household charactieristics for 1984 and 2012, the first and last years of our series.

A few points are worth detailing here. First, because the CEX and NEI use different industry definitions, we manually created a concordance to match consumption items in the CEX with the pollution intensity of industries calculated from the NEI. Since the emissions intensities (based on NAICS codes) have more categories than the CEX, most CEX codes were matched to several NAICS categories.[17] We calculated the weighted average pollution intensity based on total sales for each NAICS code.[18]

A second point involves our treatment of technology. One of the important changes explaining the decline in pollution in the United States has been technological change, or the technique effect.[19] But because here we are interested in the income-driven composition effect—the income–pollution relationship holding all else constant—one of the factors we hold constant

[15] This input-output calculation is outlined in the online appendix. See also Leontief (1970) for the original, Levinson (2009) for a more recent application, or Miller and Blair (1985) for a textbook explanation.
[16] We exclude CEX rounds prior to 1984 because this is the first year with integrated diary and interview data, and the first year with both urban and rural households included (See US Bureau of Labor Statistics, 2014).
[17] The NAICS groups industries based on similarities in production processes, whereas the UCCs used in the CEX categorize goods based on similarities in consumption patterns. The online appendix describes the matching between NAICS and CEX categories.
[18] The Economic Census measures total "sales, shipments, receipts, and revenue" and the Census of Agriculture measures the "market value of agricultural products sold" (US Census Bureau, 2014; US Department of Agriculture, 1999).
[19] See Levinson (2015) or Shapiro and Walker (2015).

is technology. We apply the same 2002 NEI-based emissions intensities to all cross sections of consumption data, regardless of year, essentially calculating the predicted amount of pollution that would be necessary to produce each households' consumption choices each year, if all industries used their 2002 technologies and associated emissions intensities.[20]

As an example, note that in table 1, the sulfur dioxide (SO_2) embodied in the typical household's consumption rose slightly between 1984 and 2012, from 117.0 to 118.2 pounds. But the national average ambient sulfur pollution fell during that same period, by 73 percent.[21] The main difference is that the change in table 1 is based only on changes in the quantity and composition of household consumption, setting aside any change in the technology used to produce those goods and services. Presumably if manufacturers and power plants hadn't used more scrubbers and cleaner coal between 1984 and 2012, actual ambient SO_2 pollution would have increased too.

A third issue concerns international trade. We use US-based emissions intensities for each industry. Readers can think of that as an assumption that all goods are manufactured in the United States, including intermediate inputs, or as an assumption that all production everywhere uses US technology with US emissions intensities, but where we account for pollution no matter where in the world it is emitted.

If we were interested in accounting for actual worldwide emissions, then our EECs that use US emissions intensities have measurement error. That error could affect the results in a number of ways. If over time Americans have been importing more from countries with higher pollution intensities, actual EECs have been shifting down less quickly than we have estimated, or might even be shifting up. That point is refuted by Levinson (2009, 2015) and Brunel (2016), which show that shifting US imports have not accounted for a significant change in US pollution.

Another way imports might affect our estimated EECs would be if high-income households typically consume more imported goods and other countries use more pollution intensive processes. In that case rich households would be responsible for more pollution than we have estimated and actual EECs in any year would be steeper or less concave. Alternatively,

[20] Others have studied how environmental regulations drive technological change, for example Popp (2002), Aghion et al. (2016), and Brunel (2017). Our focus is on consumption, so any regulation-caused change in pollution that we predict comes from changes to goods' prices or availability.
[21] www.epa.gov/air-trends/sulfur-dioxide-trends accessed July 11, 2017.

if low-income households consume more imports and other countries pollute more, then actual EECs in any year would be less steep.

To be clear, we don't know the pollution per dollar of production by foreign manufacturers, so we cannot account for that overseas pollution. By concentrating on US consumers and US emissions intensities we focus on two simpler and as yet unstudied questions: how much has US consumption shifted toward goods produced by cleaner industries, as defined by US emissions intensities, and how has that shift been divided between movements along and shifts in the EECs.

Although assembling the data to estimate indirectly generated household pollution has been complex, several aspect of EECs make their estimation simpler than traditional Engel curves. For one, estimates of traditional Engel curves must account for the obvious endogenity of income and consumption. Both income and consumption are at least partly choice variables, so it is not clear whether people choose the goods they consume based on their incomes or choose their incomes in order to purchase the goods they desire to consume. Estimating traditional Engel curves therefore involves tricky issues of identification (Blundel et al., 2007). But with EECs, we believe we are safe assuming people do not concern themselves with the pollution indirectly generated to produce the goods and services they desire when choosing how hard to work or what jobs to take. Pollution might affect their choice of goods if they are environmentally conscious but probably not their level of income. Income is thus arguably exogenous with respect to the pollution content of household consumption.

A second challenge to estimating traditional Engel curves is determining the appropriate degree of aggregation. Demand for narrow categories can vary widely across households and over time, making patterns difficult to discern. But broader categories may combine inferior and normal goods and mask the shapes of the underlying Engel curves. The Engel curve for beef may be ambiguously shaped if hamburger is a necessity and steak a luxury. When estimating EECs, however, what matters is the overall pollution created indirectly as a result of each household's consumption, not the specific consumption of individual goods or services.

One challenge that applies equally to ordinary and environmental Engel curves involves prices and quality. If richer households purchase more expensive, higher quality goods, they may spend more on those goods without consuming larger physical quantities or being responsible for more pollution. Because we estimate pollution by multiplying itemized expenditures by per-dollar pollution intensity coefficients, expensive items are assigned more pollution than inexpensive items. For example, if rich and poor households each purchase one bottle of wine, but the rich households' wine is pricier, our EECs will falsely attribute more pollution to the rich households even if both bottles were produced in the same manner. This results in a bias against finding that EECs are concave. Any concavity we find in those EECs and any share of the cleanup we attribute to that concavity can thus be interpreted as a conservative estimate.[22]

Nonparametric Estimates of Environmental Engel Curves

No theory dictates the form of the income-pollution relationship, so a natural first step is to examine the shape and structure of the EECs with as few restrictions as possible.[23] In fact, as Hausman et al. (1995) note, typical least squares or nonlinear least squares estimates of Engel curves suffer from classic errors-in variables problems. For that reason, we start here by simply plotting pollution embodied in consumption at different income levels, without running regressions of any kind. In the next section we estimate quadratic versions to account for other household demographics and regional variations, including prices, but the results there do not differ notably from these initial nonparametric versions.

We first separate households in the 1984 cross section of the CEX into 50 groups based on after-tax income, where each group represents 2 percent of the overall 1984 income distribution. We use after-tax income because otherwise changes in the shape of the Engel curve between 1984 and 2012 might be affected by changes in the progressivity of income tax policy. During that period, the top marginal federal income tax rate fell from 50 to 35 percent (US Department of the Treasury, 2016). If we ignore that decline in progressivity, along with the pollution emitted producing government goods and services, it would exaggerate the concavity of the EECs found in later years.

The next step is to calculate the average level of pollution associated with consumption by each of the 50 income groups. We start by focusing on particulate matter smaller than 10 microns (PM10) because of its significant public health consequences and importance to cost-benefit analyses, but we also show similar results for other major local air pollutants. Plotting

[22] A related problem would arise if rich and poor households face different prices for identical goods. This could work in either direction. Rich people might face higher prices in costly metropolitan areas, or lower prices thanks to more local competition or the ability to price shop.

[23] Common approaches others have taken range from simply plotting the data to nonparametric kernel estimation (Lewbel, 1991; Hausman et al. 1995).

these 50 points with income on the horizontal axis and pollution on the vertical axis yields a non-parametric EEC for 1984. This EEC for PM10 is shown as the top line in figure 1. Average pollution is calculated using the 2002 emissions intensity coefficients, so this EEC represents the pollution associated with household consumption in 1984 if all goods and services were produced in the United States using 2002 production technology. A household in the median income bin (earning $30,636 to $31,828 after taxes, measured in 2002 dollars) would have been indirectly responsible for an average of 11.14 pounds of PM10.[24]

To observe how the EEC relationship may be evolving over time, figure 1 also depicts a second EEC estimated using the 2012 CEX. To keep the two curves directly comparable, we use the same income bin cutoff values in the 2012 EEC as are used in the 1984 EEC.[25] Households with 2012 after-tax income in the 1984 median bin ($30,636 to $31,828) would have been indirectly responsible for 9.91 pounds of PM10 on average, 11 percent less than households with the same income in 1984.

Three phenomena are apparent from the EECs in figure 1. First, richer households are responsible for more overall pollution. This is not surprising since richer households spend more on consumption and therefore have more pollution created as a result of producing the goods and services they consume.

Second, EECs have income elasticities less than one. This means that richer households consume less pollution-intensive mixes of goods and services, even if they are responsible for more overall pollution. Under standard definitions, goods whose consumption increases with income are "normal," and goods whose consumption increases less than one-for-one are considered "necessities." Pollution, according to these EECs, is a necessity.[26] Although much of the concavity appears at the top of the income distribution, rich households account for more spending. As a result, the slope and concavity depicted in figure 1 have large effects on overall

[24] This estimate only includes emissions from point sources measured in the NEI. It does not include area or mobile sources.

[25] Note that each point of the 2012 EEC does not therefore represent an equal number of households. Income growth between 1984 and 2012 led to a rightward shift of the income distribution, but because we use income bins based on the 1984 income distribution, relatively fewer households fall in low bins and relatively more households fall in higher bins: 17 percent of households in 2012 fall into the first 10 bins (the bottom 20 percent of the 1984 income distribution) and 27 percent of households in 2012 fall into the top 10 bins (the top 20 percent of the 1984 income distribution). Figure A.12 in the online appendix compares the shares of households in each bin for both 1984 and 2012.

[26] Of course households are not choosing pollution directly. Pollution is an incidental byproduct of the goods households do choose, so it may not be accurate to call pollution a "necessity." It might be more accurate, if awkward, to say that goods and services that generate relatively more pollution are, on average, necessities.

pollution, as we show later. And in fact, concavity in figure 1 may be understated if richer households consume more expensive versions of the same goods.

Third, figure 1 suggests that EECs are shifting down over time. The shape and concavity are generally consistent in both years, but households represented by the 2012 EEC are responsible for less pollution than their 1984 counterparts with similar real incomes. This downward shift is not due to improvements in technology or abatement because both curves use the same 2002 emissions intensities. Instead, the downward shift in figure 1 reflects a change in consumption composition due to some combination of changing prices, regulations, or social norms.

To test the sensitivity of the EECs to the use of after-tax income, we repeat the analysis using pre-tax income on the horizontal axis in figure 2. If anything, the pre-tax EECs look less concave and have shifted down less over time. Perhaps the overall income tax system in the US is not progressive enough to affect the shapes of the curves.[27]

In figure 3 we plot these same nonparametric EECs (pollution against 1984 and 2012 after-tax income) for four other common air pollutants: volatile organic compounds (VOCs), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon monoxide (CO). All are similarly increasing, concave, and shifting down over time.

One drawback of the otherwise flexible approach to estimating EECs depicted in figures 1 and 2 is that they do not account for additional demographic factors related to household consumption. Standard Engel curves can vary with consumer characteristics (Lewbel, 2008). In our context, those other characteristics may account for both the shape of EECs and their changes over time. In any year, richer households consume a less pollution-intensive mix of goods and services, but they also have different household sizes, ages, etc. And over time households appear to have consumed a less pollution-intensive mix of goods and services, but average household sizes, ages, and locations also changed.

Another possible concern with the nonparametric approach in figures 1 and 2 is that the “law of one price” may not hold. If some regions of the country have higher household incomes and higher relative prices for goods that require more pollution to produce, then our curves conflate income elasticities and price changes. Or, if incomes and relative prices have changed

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[27] In other tests we repeated the analysis using consumption on the horizontal axis rather than income. The results are qualitatively similar: EECs are upward sloping, have income elasticities less than one, and shift down over time. See online appendix figures A.8 and A.9.

over time at different rates in different regions, then our division of the cleanup into movements along and shifts in Engel curves may be biased by price effects.

Table 1 reports some of these key household characteristics along with estimated indirect pollution. Between 1984 and 2012 the average indirect PM10 emissions decreased almost imperceptibly (from 11.69 pounds to 11.27 pounds), while average real after-tax income increased 19 percent (from \$37,797 to \$45,094). At the same time, the average household became older, smaller, better educated, more urban, less likely to be married, and more likely to live in the South and West. To assess whether these demographic changes and regional variations account for the shape and movements in the EECs, we turn to parametric estimations.

Parametric Estimates of Environmental Engel Curves

To account for household characteristics aside from income that affect the quantity and mix of goods and services consumed, we begin by estimating a series of quadratic linear regressions with household pollution on the left-hand side and after-tax income, income squared, and other covariates on the right-hand side:

$$\mathrm{P}_{it} = \alpha_t Y_{it} + \beta_t Y_{it}^2 + \boldsymbol{X_{it}\delta_t} + \varepsilon_{it} \qquad (1)$$

where P_{it} and Y_{it} are pollution and after-tax income associated with individual households in the CEX, and X_{it} is a vector of other covariates. The coefficients are indexed by *t* because we run separate regressions for each year to obtain a set of annual coefficients.

Column (1) of table 2 shows a version of that regression for PM10 pollution with only the after-tax income quadratic, excluding all the other household characteristics, using the 1984 cross section of the CEX. The estimated shape is concave and the negative coefficient on income squared (–0.03) is statistically significant.[28]

The second column of table 2 adds additional control variables for age, household size, marital status, indicators for race and education of the household head, and regional indicators that control for relative price differences.[29] Nearly all covariates are statistically significantly correlated with total PM10. Overall, the results suggest that households that are larger, older, married, more educated, non-black, and located in the South were indirectly responsible for more

[28] We also explored other nonlinearities such as cubic polynomials and logarithmic specifications. The results (available from the authors) are consistent: EECs are upward sloping, have elasticities less than one, and shift down over time.
[29] For now we include only the four Census regions. Later we discuss adding state indicators, which are only available in the CEX starting in 1993.

pollution. Including these additional household characteristics does appear to change the shape of the EEC. The estimated EEC is still upward sloping, but is less steep and not concave.

The change in the EECs between columns (1) and (2) of table 2, with the addition of covariates, raises concerns about omitted variable bias. Higher-income households might be responsible for less pollution per dollar of consumption because they are educated, which we control for, or for some other reason we are missing. To address this, in what follows we estimate all of our results two ways: first with only income and income squared as in column (1); and second with a full set of covariates as in column (2). And as we will show, adding the extra observable covariates does not change our fundamental conclusions about the shapes of the curves, how they change over time, or the decomposition of pollution changes into movements along and shifts in EECs between 1984 and 2012.[30]

To compare these parametrically estimated EECs across time, columns (3) through (5) of table 2 repeat the regression from column (2) using the 1994, 2005, and 2012 cross sections of the CEX. Column (6) of table 2 shows the difference between coefficients in 1984 and 2012 (from columns (2) and (5)) and indicates whether there is a statistically significant difference. Household size, and age had a smaller effect on pollution in 2012 relative to 1984, whereas household size squared, age squared, race being Black, and race being Other had larger effects.[31]

Figure 4 plots the predicted relationship between income and PM10 pollution based on the EECs estimated in table 2. The two thick lines—one solid and one dashed—are based on columns (2) and (5) of table 2. Each is drawn by fixing the other covariates aside from income at their average values for their respective years. These parametrically estimated EECs plot income expansion paths holding other observable household characteristics constant. They have similar characteristics to the nonparametric EECs in figure 1: they are upward-sloping, shift down over

[30] To formalize this, we also have estimated a version of the approach developed by Altonji et al (2005) as refined by Oster (2017). Oster notes that, under some restrictive assumptions about the relationship between observed and unobserved covariates, the coefficients from the short and long regressions in columns (1) and (2) of table 2, along with their R-squareds, can be used to approximate the true coefficients from a hypothetical regression using a full set of observed and unobserved covariates. In our case, the results suggest that column (2) provides a reasonable estimate of the causal effect of income on pollution, even after taking into account other observed and unobserved household characteristics.

[31] Over the entire 29-year period the income coefficient remains about steady, and slightly greater than 1.0 for PM10. The coefficient on income squared becomes more precisely estimated over time, and is marginally significantly negative throughout the latter half of the period. To see all 29 pairs of coefficients, see Appendix figure A.11.

time, and have elasticities less than one. In addition, the curves become increasingly concave in more recent years.

To demonstrate what adding covariates does to the parametric EECs, the two thin lines in figure 4 plot regressions of pollution on income and income squared alone: column (1) of table 2 for 1984 and its analog (not shown) for 2012. Although adding the covariates does change their shape somewhat, the basic results remain. The EECs are upward sloping, shift down over time, and become increasingly concave.

Table 3 shows coefficient estimates for quadratic EECs for four other common air pollutants, VOCs, NO_x, SO_2, and CO, using the 1984 and 2012 CEX. We calculate total emissions due to household consumption using the same technique as in table 2 and the same set of demographic control variables. In all cases, the coefficient on after-tax income is positively and statistically significant. Similar to PM10, the effect of after-tax income squared is not significant in 1984 but becomes negative and significant by 2012. Further, the sign and significance of other covariates is consistent with the PM10 EEC. The hallmark attributes of the individual PM10 EECs—upward sloping, becoming more concave, and shifting down over time—are also exhibited by other common air pollutants.

Figure 5 depicts versions this same relationship for these other air pollutants. VOCs, NO_x, SO_2, and CO all exhibit similar income expansion paths to that of PM10. And, as with PM10, adding the demographic covariates does not change the results.

Out of concern that the four Census region indicators in tables 2 and 3 might not sufficiently account geographic difference, including relative prices, we have also estimated all of the models using state fixed effects. State indicators only became available in the CEX starting with 1993, so we lose the first 11 years of data. The income coefficients for all pollutants can be found summarized in the online Appendix, Table A.2. The coefficients on income and income square are not notably different from those with the regional fixed effects, and the basic results remain. Engel curves become flatter and shift down over time.

The two approaches so far represent extremes of parameterization. Figures 1 and 3 plot means of pollution by income group, assuming no functional form. At the other extreme, figures 4 and 5, assume pollution follows a quadratic function of income, controlling for other household characteristics. As an intermediate case, we have also estimated all of the EECs using restricted cubic splines, using five spline knots (Harrell 2001) rather than the income quadratic. Graphs of the splines look similar to both the nonparametric and quadratic specifications: EECs are upward sloping, have elasticities less than one, and shift down over time.[32]

Finally, some readers have observed that consumption choices made early in people's lives may persist, either because the goods purchased are long-lived durables, or because people develop habits. In other words, EECs for individuals whose incomes grow over time may not be as flexible or concave as a hypothetical EEC comparing two identical individuals with different incomes. We address this in two ways. First, in all of the parametric specifications, we include the age and age squared of the household head. That way, to the extent the specification is correct, we our plotted EECs compare the pollution consequences of consumption choices by people with identical ages but different incomes. And second, we repeated all of the analysis, parametric and nonparametric, limited to cases where the heads of household is in the youngest fourth of the age distribution, less than 34.5 years old. Incomes are lower, unsurprising, but the basic results persist. EECS have positive slopes, elasticities less than one, and shift down over time.[33]

An Application: Decomposing the Composition Effects

Movements along and shifts in the EECs affect the level of pollution embodied in the goods and services consumed by households, but there is an important distinction between the two effects. Movements along the EEC depend on underlying preferences of richer households relative to poorer households, all else equal. They are independent of any particular environmental policy intervention. In this sense, movements along an EEC may be predictive of future levels of pollution under status quo environmental regulations if household incomes increase but nothing else changes.

In contrast, shifts in the EEC are the direct result of evolving aggregate preferences or environmental policies that change the relative supply and demand for pollution-intensive goods. There is no reason to expect the environmental benefits of downward shifting EECs to continue without the accompanying change in preferences or tightening of environmental policy.

Comparing annual sets of EECs allows us to decompose changes in this indirect household pollution into a component due to income growth (a movement along the EEC) and a

[32] Plots of the restricted cubic splines are in the online appendix figures A.13 and A.14.
[33] Available separately from the authors.

component due to aggregate conditions (a shift in the EEC). For example, we could use the 1984 EEC to assign a hypothetical level of total PM10 to each household in 2012. This would tell us how much pollution to expect if the EEC was fixed based on 1984 conditions, but households move along the EEC as their incomes change. The difference between this hypothetical level of PM10 and the actual emissions (holding production technology constant) is due to shifts in the EEC between 1984 and 2012.

The Oaxaca-Blinder decomposition provides a means of separating these components while holding other demographic changes constant.[34] Define the average level of pollution in a given year based on the regressions from table 2:

$$\overline{\mathrm{P}}_t = \alpha_t \bar{Y}_t + \beta_t \overline{Y_t^2} + \overline{\mathbf{X}}_t \boldsymbol{\delta}_t \tag{2}$$

where $\overline{\mathrm{P}}_t$ is average indirect pollution, $\bar{Y}_t$ and $\overline{Y_t^2}$ are average income and income squared, and $\overline{\mathbf{X}}_t$ is the average of other included covariates. The error term disappears because the average OLS error is zero by construction.

The change in average pollution between 1984 and 2012 can then be written as:

$$\begin{aligned} \overline{\mathrm{P}}_{12} - \overline{\mathrm{P}}_{84} = \alpha_{12} \bar{Y}_{12} + \beta_{12} \overline{Y_{12}^2} + \overline{\mathbf{X}}_{12} \boldsymbol{\delta}_{12} \\ -\alpha_{84} \bar{Y}_{84} - \beta_{84} \overline{Y_{84}^2} - \overline{\mathbf{X}}_{84} \boldsymbol{\delta}_{84} \end{aligned} \tag{3}$$

By adding and subtracting $\alpha_{84} \bar{Y}_{12} + \beta_{84} \overline{Y^2}_{12} + \overline{\mathbf{X}}_{12} \boldsymbol{\delta}_{84}$ and grouping terms, we have:

$$\begin{aligned} \overline{\mathrm{P}}_{12} - \overline{\mathrm{P}}_{84} = \alpha_{84} \left(\bar{Y}_{12} - \bar{Y}_{84}\right) + \beta_{84} \left(\overline{Y_{12}^2} - \overline{Y_{84}^2}\right) \\ +(\alpha_{12} - \alpha_{84}) \bar{Y}_{12} + (\beta_{12} - \beta_{84}) \overline{Y_{12}^2} \\ +\bar{X}_{12}(\delta_{12} - \delta_{84}) + (\bar{X}_{12} - \bar{X}_{84}) \delta_{84} \end{aligned} \tag{4}$$

The first two terms in equation (4) capture the effect of changing income on total point-source air pollution, holding constant the 1984 OLS coefficients. This is equivalent to a movement along the 1984 EEC. The second two terms capture the effect of the changing coefficients on income and income squared. This is equivalent to a shift (or change in shape) of the EEC. Finally, the last two terms account for changes in all other covariates, including demographics, migration, and household size, and their changing coefficients.

Table 4 presents the results of this decomposition. Consider column (1), for PM10. Each entry is calculated by multiplying the change in average values of the variable (column (3) of

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[34] Oaxaca (1973) and Blinder (1973). For additional discussion of decomposition techniques, see also Fortin, Lemiuex, and Firpo (2010).

table 1) by the 1984 OLS coefficients (column (2) of table 2) and represents the change in pollution predicted by the change in that particular variable, holding all else constant, including technology. At the bottom of table 4 we have grouped these effects into those due to after-tax income, or movement along the EEC, and those due to other covariates. The level of total particulates (PM10) embodied in the average household's consumption decreased by only 0.42 pounds between 1984 and 2012 (from table 1). Changes in average after-tax income and income squared led to a hypothetical increase of 0.88 pounds (0.82 increase from after-tax income and 0.06 increase from after-tax income squared). At the same time, changing demographics would have led to an additional increase of 0.12 pounds. The remaining difference, 1.42 pounds, is attributable to shifts in the EEC.

Columns (2) through (5) of table 4 present similar analyses for VOC, NO_x, SO_2, and CO. The scale effects and offsetting compositional shifts due to changes in average after-tax income resulted in increases in emissions (1.71 pounds, 4.82 pounds, 8.09 pounds, and 3.84 pounds, respectively). Like the case of PM10, these increases were all boosted further by the effects of demographic changes. The remaining portions of the total changes for each pollutant in table 4 were large, ranging from 5.74 pounds for VOC to 11.09 pounds for CO. For none of the pollutants, however, do the overall demographic changes other than income have substantial effects on total pollution, listed at the bottom of table 4; the pollution effects of the movements along and shifts in the EECs are much larger.

The increases in emissions due to changes in household income, such as the 0.88 pound increase in PM10, can be further decomposed into separate household-level scale and composition components. Along a given EEC, richer households consume more goods and services overall, but they also consume a less pollution-intensive mix relative to poorer households. The balance of these two effects depends on the shape of the EEC. To the extent that EECs are inelastic, the compositional component is stronger and households with higher income are responsible for proportionally less pollution. This effect becomes more pronounced as EECs become increasingly concave. On the other hand, if EECs were not inelastic, a pure scale effect would cause pollution to grow at the same rate as income.

Figure 6 depicts the relative magnitude of these effects for PM10 over time by applying the same decomposition to all interim years between 1984 and 2012. The top line depicts the level of pollution that would occur if the proportions of goods and services households consumed remained constant as household incomes grew. That is the scale effect at the household level.[35] Line (2) captures the hypothetical effect of movements along the 1984 EEC. The vertical difference between these two lines is the offsetting compositional effect reflected in the inelastic shape of EECs. Line (3) shows the contribution of changing demographics in addition to changing income and falls slightly above the second line because the balance of other factors, such as household size, education, and geography, led to a slight net increase in the pollution intensity of consumption.

The bottom line of figure 6 shows the predicted level of pollution in each year calculated by pairing the 2002 emissions intensity coefficients with each round of the CEX expenditure data. This is the level of pollution that would occur if technology were fixed based on 2002 emissions intensities, but where we account for the true mix of goods and services consumed by households in each period. The vertical distance between lines (3) and (4) is due to downward shifts in the EEC over time.

Table 5 presents the calculations behind figure 6, decomposing household consumption-related pollution changes between 1984 and 2012 into those due to the scale of after-tax income growth, movements along the EEC, shifts in the EEC, and other demographic changes. Column (1) repeats the predicted change in household pollution from table 1, holding technology fixed using 2002 emissions intensities. Four of the five pollutants decline, and SO_2 increases only slightly. For PM10, the decline is just 0.42 pounds, depicted as the bottom line of figure 6. The second column of table 5 describes the household-level scale effect. Between 1984 and 2012 average household after-tax income increased 19 percent. That's the top line of figure 6. With no compositional shift in consumption, we would expect emissions of each pollutant in table 5 to also increase by 19 percent. In the case of PM10, that means an increase of 2.26 pounds per household. The difference between columns (1) and (2)—2.68 pounds of PM10—represents the reduction in pollution collectively explained by movement along the 1984 EEC, changes in household demographics, or shifts in the EECs over time.

[35] A curious feature of the CEX data is that real household incomes did not grow between 1984 and 1995. Hence all of the changes we describe in Table 5 stem from income growth during the last half of the sample period. The changes also include the decrease in income observed in later years. But the predicted changes in household-level pollution coming from movements along the Engel curves are derived from comparisons across households with different incomes in 1984. See the online appendix for a comparison of income measured in the CEX to that reported by the Congressional Budget Office and in the Current Population Survey.

The difference between the 2.26 pound increase in PM10 and our movement-related estimate of 0.88 from table 4 represents the mitigating effect of compositional shifts along the 1984 EEC. In this case, compositional changes in consumption along the EEC offset 1.38 pounds of PM10 from the scale effect, reported in column (4) of table 5. In total, the sum of the compositional offsets (-1.38 from movement along the EEC and -1.41 pounds from shifts in the EEC) together with the effects of demographics (+0.12 pounds) counteract the scale effect (2.26 increase) to equal the overall predicted change of -0.42 pounds. Those changes are depicted in figure 6 as lines (2) and (3).

All five major air pollutants exhibit similar patterns in table 5. Total emissions predicted by household consumption declined or only increased slightly (column 1), even though emissions would have grown substantially if they had increased one-for-one with household income (column 2). That difference (column 3) is partly offset by the fact that EECs are inelastic. Pollution predicted by consumption doesn't increase one-for-one with income (columns 4 and 5). The difference is mostly unaffected by demographic changes (columns 6 and 7). And the difference is partly explained by downward shifts in the EECs. Households with similar income and demographics consume a less pollution-intensive mix of goods and services in 2012 than they did in 1984 (columns 8 and 9).

A key conclusion from table 5 is that movements along the EECs and shifts in the EECs are roughly equally responsible for reductions in household pollution relative to a pure scale effect. This can be seen by comparing columns (4) and (8), which set aside the demographic changes in column (6) and the technique changes that are held constant throughout. Column (4) contains the pollution reduction due to movements along the EEC, and column (8) contains the pollution reductions due to shifts in the EEC between 1984 and 2012. They are of roughly similar magnitudes. Columns (5) and (9) of table 5 express these two effects—movements and shifts—as percentages of the overall pollution decline to be explained in column (3). We find that movements along EECs explain 27 to 68 percent of the overall compositional effect and shifts in the EECs explain 39 to 76 percent. But the fundamental insight is similar across pollutants. Changes in the goods and services households consumed between 1984 and 2012 were responsible for large declines in the pollution those households were indirectly responsible for. And those changes are about evenly split between those due to growing household incomes along inelastic EECs and those due to downward shifts of the EECs over time.

We have also estimated a version of table 5 and figure 6 where the “movement along” calculation is based on EECs estimated from the quadratic in income alone, as in column (1) of table 2. That line overlies lines (2) and (3) in figure 6, and we have included the figure in the Appendix (figure A.10). Adding the demographic covariates does not change the conclusion that consumption-related changes in the composition of polluting goods in the US can be divided about equally between movements along and shifts in EECs.

Figures analogous to figure 6 drawn for the other four pollutants in table 5 make the same point.[36] Shifts in the mix of goods and services consumed by the average household have more than offset any pollution increase due to growth in household income. About half of those composition changes come solely from the fact that richer households consume a less pollution-intensive mix of goods, and the other half comes from the fact that households at every income level consume a less pollution-intensive mix in 2012 than they did in 1984.

Discussion

Half of the decline in indirect air pollution from US household consumption comes from downward shifts in EECs. Can that be attributed to environmental regulations? Perhaps. It is not attributable to regulations’ effects on emissions intensities, because throughout we have held emissions intensities constant at their 2002 levels, the midpoint of our time series. This is in the spirit of Engel curves holding all else equal. But the downward shift we see over time might be the indirect effect of regulations through their effects on relative prices. If regulations increase the relative prices of goods whose production emits more air pollution, and households respond by consuming less of those more expensive goods, that could account for part of why our estimated EECs shift down over time.

More generally, the EECs we estimate help put broad changes in the US environment into context. Over the past 30 years, air pollution in the United States has declined despite increases in total production. Some of this improvement has come from employing cleaner production technologies in cars and factories, but much of it comes as a result of consuming a cleaner mix of goods and services. How much of this cleaner consumption has been a consequence of economy-wide trends, such as regulation-induced price changes, and how much comes from coincidental preference by richer households for cleaner goods? Environmental

[36] Figures A.4 through A.7 in the online appendix.

Engel curves describing the relationship between income and the pollution-intensity of household consumption provide a means for comparing these two effects.

Whether estimated parametrically or non-parametrically, EECs display three key characteristics: they are increasing, have elasticities less than one, and are shifting down and becoming more concave over time. These characteristics allow us to decompose changes in the pollution associated with household consumption into movements along the EEC and shifts in the EEC. Between 1984 and 2012 we find that compositional changes in consumption due to movements along EECs and downward shifts of EECs more than offset the 19 percent increase in real household incomes. For five common air pollutants, about half the overall offsetting compositional effect was due to movements along EECs and the other half to shifts in the EECs.

A few caveats deserve mention. We study only criteria air pollutants, the ones documented most thoroughly by the NEI and the ones that have been the focus of most decomposition analyses. That focus omits pollution coming from non-point sources (such as vehicles), other media (water pollution), and all other types of air pollution (toxins, CO_2). We cannot be sure other pollutants follow the patterns we observe for the criteria air pollutants, but given how highly correlated the EECs are for the five pollutants we do study, we suspect similar conclusions would apply.

In the end, this decomposition of pollution changes into movements along and shifts in EECs represents just one aspect of the environmental consequences of economic growth. A large portion of the cleanup in the United States comes from changes in technology, but a significant fraction comes from the changing composition of production. If changing import composition does not account for that changing production, then it must come from consumption. Isolating the consumption-related compositional changes in pollution suggests that household-level composition changes have more than offset the increased pollution from growing household incomes.

In understanding the offsetting effect of compositional changes, the distinction between movements along and shifts in EECs is critical. An important reason pollution in the United States has not increased one-for-one with income growth is that households have moved away from pollution-intensive goods and services. Our analysis shows that this change is not entirely automatic. Rich households in any given year do consume a proportionally less pollution-intensive mix of goods than lower-income households. Given higher incomes and no other changes, 1984 households would have consumed a cleaner mix of goods, and that accounts for about half of the overall reduction. But households with the same real incomes also consumed a cleaner mix of goods in 2012 than in 1984, an improvement that accounts for an approximately equal reduction, and one that must come from changes to aggregate conditions such as prices, social norms, or environmental policies.

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Table 1. Average Values for Selected Variables

Variable	Cross section 1984	Cross section 2012	Difference
	(1)	(2)	(3)
Pollutant (pounds, 2002 technology)			
Particulate matter less than 10 microns (PM10)	11.69	11.27	-0.42
	(0.15)	(0.11)	(0.19)
Volatile organic compounds (VOCs)	19.62	15.82	-3.80
	(0.30)	(0.21)	(0.36)
Nitrogen oxides (NO_x)	72.27	69.56	-2.72
	(0.89)	(0.64)	(1.09)
Sulfur dioxide (SO_2)	117.00	118.20	1.17
	(1.51)	(1.10)	(1.86)
Carbon monoxide (CO)	44.65	37.88	-6.78
	(0.68)	(0.52)	(0.86)
After-tax income (10,000 2002 $)	3.78	4.51	0.73
	(0.06)	(0.07)	(0.09)
Household size	2.71	2.50	-0.22
	(0.03)	(0.03)	(0.04)
Age of household head	47.03	50.00	2.98
	(0.38)	(0.32)	(0.50)
Head is married (share of pop.)	0.604	0.506	-0.098
Race of head is Black (share of pop.)	0.107	0.115	0.008
Education of head (share of population)			
Elementary only	0.293	0.130	-0.162
High school	0.299	0.244	-0.055
Some college	0.201	0.296	0.095
College	0.106	0.209	0.103
More than college	0.102	0.121	0.019
Region (share of population)			
Northeast	0.183	0.179	-0.004
Midwest	0.219	0.212	-0.008
South	0.261	0.374	0.113
West	0.169	0.225	0.056
Rural	0.167	0.082	-0.085
Observations	3,184	3,538	

Notes: Values calculated using sample weights. Standard errors are shown in parentheses. Differences may not match exactly due to rounding. Nominal income values are adjusted using the CPI for all items; nominal expenditure values are adjusted using the corresponding price series for food and beverages, gasoline, electricity, fuel oil, and core expenditure. Regional designations in the 1984 CEX only include non-rural households; regional designations in the 2012 CEX include all households.

Table 2. Parametric Environmental Engel Curves for PM10

Dependent variable:	**1984**		**1994**	**2005**	**2012**	**Coefficient change 1984 to 2012**
Pounds PM10 per household	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
After-tax income (10,000 2002 $)	1.950	1.124	0.947	1.103	0.997	-0.127
	(0.132)	(0.154)	(0.145)	(0.110)	(0.087)	(0.177)
After-tax income squared	-0.0317	0.0045	0.0019	-0.0107	-0.0191	-0.0236
	(0.0119)	(0.0119)	(0.0131)	(0.0065)	(0.0053)	(0.013)
Household size		2.321	2.125	2.476	1.671	-0.65
		(0.232)	(0.250)	(0.249)	(0.210)	(0.313)
Household size squared		-0.158	-0.145	-0.202	-0.0786	0.0794
		(0.0255)	(0.0326)	(0.0289)	(0.0269)	(0.037)
Age		0.265	0.240	0.185	0.160	-0.105
		(0.0337)	(0.0333)	(0.0329)	(0.0314)	(0.046)
Age squared		-0.00238	-0.00206	-0.00135	-0.00111	0.00127
		(0.00032)	(0.00032)	(0.00030)	(0.00031)	(0.000)
Married		0.746	1.247	1.282	0.995	0.249
		(0.291)	(0.251)	(0.285)	(0.219)	(0.364)
Race: Black		-1.891	-0.942	(0.336)	-0.783	1.108
		(0.275)	(0.283)	-3.016	(0.272)	(0.387)
Race: Asian		-0.856	-1.902	(0.489)	-1.777	-0.921
		(0.950)	(0.677)	-0.362	(0.341)	(1.009)
Race: Other		-2.324	1.714	(0.634)	-0.182	2.142
		(0.718)	(1.151)	1.189	(0.623)	(0.951)
Education: High school		1.147	0.861	(0.270)	1.178	0.031
		(0.303)	(0.260)	1.103	(0.246)	(0.390)

(Continued on next page)

Table 2 (continued)

	1984		1994	2005	2012	Change 1984 to 2012
	(1)	(2)	(3)	(4)	(5)	(6)
Education: Some college		1.487	1.431	1.583	1.430	-0.057
		(0.305)	(0.306)	(0.297)	(0.241)	(0.389)
Education: College		1.821	1.657	2.058	1.677	-0.144
		(0.455)	(0.366)	(0.390)	(0.314)	(0.553)
Education: Graduate		1.978	1.907	1.495	2.411	0.433
		(0.456)	(0.435)	(0.522)	(0.464)	(0.651)
Region: Midwest		0.060	-0.642	-0.653	-0.644	-0.704
		(0.325)	(0.296)	(0.271)	(0.251)	(0.411)
Region: South		1.498	1.136	1.724	0.922	-0.576
		(0.339)	(0.288)	(0.287)	(0.253)	(0.423)
Region: West		-0.447	-0.126	1.332	-0.005	0.442
		(0.334)	(0.304)	(0.384)	(0.271)	(0.430)
Rural		0.536	0.767	-0.670	0.049	-0.487
		(0.353)	(0.367)	(0.319)	(0.338)	(0.489)
Constant	5.015	-5.553	-4.393	-4.985	-2.898	2.655
	(0.305)	(0.879)	(0.845)	(0.893)	(0.769)	(1.168)
Income elasticity at median	0.510	0.335	0.286	0.335	0.281	
	(0.020)	(0.026)	(0.022)	(0.023)	(0.018)	
F-test of income coefficients	483.4	165.5	147.5	153.3	188.5	
Observations	3,214	3,184	2,923	3,703	3,538	
R-squared	0.407	0.520	0.459	0.381	0.410	

Notes: Robust standard errors shown in parentheses. Race dummies omit "white," education dummies omit "less than high school," and regional dummies omit "northeast." Regional designations in the 1984 and 1994 CEX only include non-rural households; regional designations in the 2005 and 2012 CEX include all households. Total household pollution is calculated by multiplying itemized household consumption with the pollution intensity of production for each type of good and summing for each household. Total point-source air pollution includes upstream pollution based on a Leontief input-output calculation. All figures are calculated using 2002 production technology to estimate pollution. Nominal income values are adjusted using the CPI for all items; nominal expenditure values are adjusted using the corresponding core, food and beverage, gasoline, electricity, and fuel oil CPIs. Income elasticities are calculated at the annual median value of after-tax income, with all other variables fixed at their annual means.

Table 3. Parametric EECs for Other Air Pollutants

Dependent variable (pounds):	VOC		NO_x		SO_2		CO	
	1984	2012	1984	2012	1984	2012	1984	2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After-tax income (10,000 2002 $)	2.281	1.857	6.720	6.020	10.450	9.527	5.961	4.622
	(0.337)	(0.161)	(0.838)	(0.470)	(1.479)	(0.840)	(0.685)	(0.417)
After-tax income squared	0.0034	-0.0349	-0.007	-0.125	0.036	-0.188	-0.040	-0.092
	(0.0256)	(0.0106)	(0.066)	(0.028)	(0.116)	(0.049)	(0.055)	(0.025)
Other regressors: Household size, Age, Married, Race, Education, Region	yes	yes	yes	yes	yes	yes	yes	yes
Income elasticity at median	0.402	0.382	0.311	0.270	0.308	0.254	0.437	0.393
	(0.035)	(0.023)	(0.023)	(0.016)	(0.025)	(0.017)	(0.030)	(0.027)
F-test of income coefficients	126.9	205	184.8	216.8	160.8	168.6	161.7	154.8
Observations	3,184	3,538	3,184	3,538	3,184	3,538	3,184	3,538
R-squared	0.413	0.364	0.555	0.456	0.521	0.409	0.403	0.317

See notes for table 2. The full set of coefficients is available in online appendix table A.1.

Table 4. Movement along Parametric EECs for Air Pollutants 1984–2012

	Increase in Pollution due to movement along an EEC (pounds)				
Dependent Variable:	**PM10**	**VOC**	**NO_x**	**SO_2**	**CO**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
After-tax income (10,000 2002 dollars)	0.820	1.665	4.903	7.625	4.350
	(0.150)	(0.318)	(0.852)	(1.419)	(0.726)
After-tax income squared	0.058	0.043	-0.084	0.465	-0.509
	(0.154)	(0.329)	(0.847)	(1.495)	(0.703)
Household size	-0.500	-0.669	-3.047	-4.979	-1.487
	(0.110)	(0.171)	(0.667)	(1.101)	(0.383)
Household size squared	0.20	0.273	1.186	2.029	0.702
	(0.058)	(0.097)	(0.343)	(0.585)	(0.232)
Age	0.788	1.354	5.101	8.033	3.225
	(0.165)	(0.317)	(1.033)	(1.686)	(0.733)
Age squared	-0.661	-1.224	-4.139	-6.626	-2.896
	(0.147)	(0.295)	(0.906)	(1.491)	(0.677)
Married	-0.073	-0.176	-0.455	-0.749	-0.405
	(0.030)	(0.061)	(0.172)	(0.297)	(0.151)
Race dummies	-0.038	0.014	-0.273	-0.615	-0.133
Education dummies	0.304	0.485	2.140	3.433	0.905
Regional dummies	0.099	0.173	0.429	0.803	0.561
Total change due to income (movement along EEC)	0.88	1.71	4.82	8.09	3.84
Total change due to other demographics	0.12	0.23	0.94	1.33	0.47
Unexplained difference (shift in EEC)	-1.42	-5.74	-8.48	-8.25	-11.09

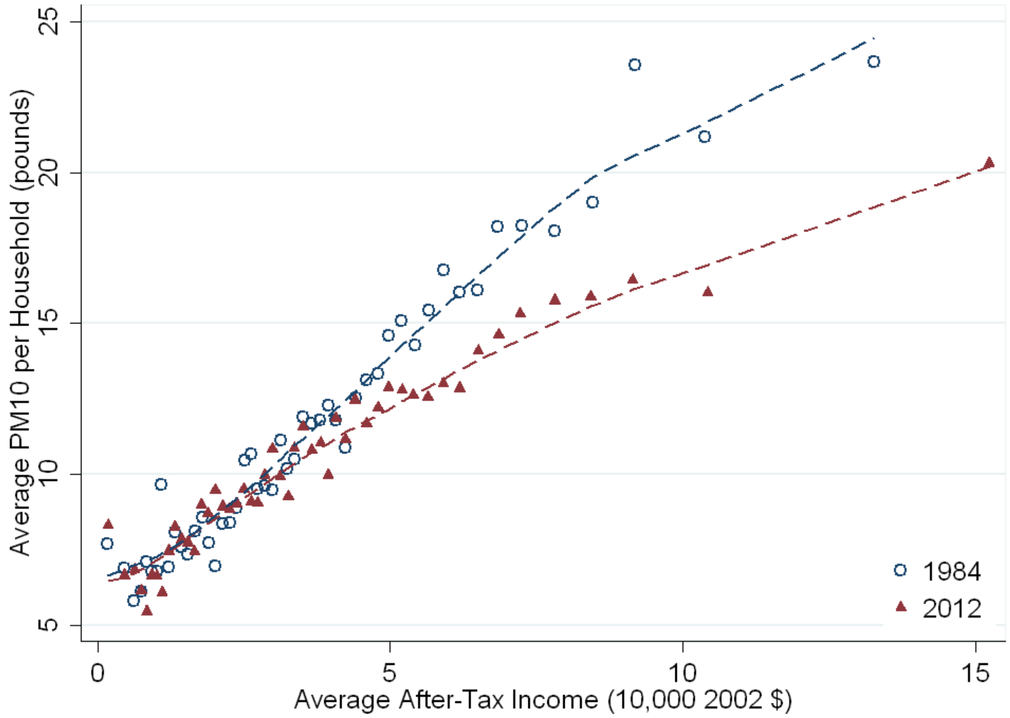
Notes: Estimates are based on Oaxaca-Blinder decompositions. Robust standard errors shown in parentheses. Movement along each EEC can be calculated by multiplying the coefficients in tables 2 and 3 by the corresponding changes in table 1. Total changes are calculated by summing the individual changes of relevant variables and may not match due to rounding. Pollution is estimated based on 2002 production technology for all years. Values for race, education, and regional indicators are the combined effect for each category.

Table 5. Pollution Offset Due to Compositional Changes in Household Consumption
Summary of Local Air Pollutants

	Total change (pounds)	Scale increase (pounds)	Total spread (2) – (1)	Offset by movement along EEC		Offset by demographic changes		Offset by shifts in EEC	
				Pounds	Share of spread	Pounds	Share of spread	Pounds	Share of spread
Pollutant	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
PM10	-0.42	2.26	2.68	1.38	0.52	-0.12	-0.044	1.41	0.53
VOC	-3.80	3.79	7.59	2.08	0.27	-0.23	-0.030	5.74	0.76
NO_x	-2.72	13.95	16.67	9.13	0.55	-0.93	-0.056	8.47	0.51
SO_2	1.17	22.58	21.41	14.49	0.68	-1.33	-0.062	8.25	0.39
CO	-6.78	8.62	15.40	4.78	0.31	-0.47	-0.031	11.09	0.72

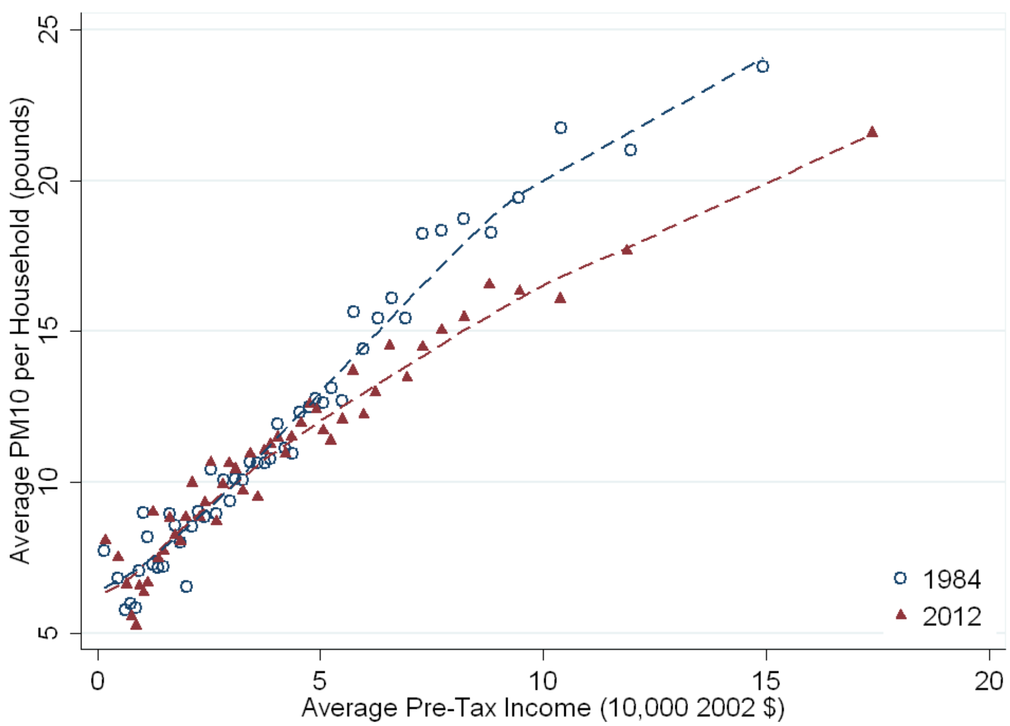
Notes: The total change in pollution is predicted using CEX and NEI data, based on 2002 production technology. The scale increase in pollution is calculated by multiplying pollution levels in 1984 by the proportional increase in after-tax income between 1984 and 2012. The total spread is calculated as the difference between the predicted change from the NEI-based pollution coefficients and the predicted increase due to the scale effect. Offsets in column (4) are calculated by subtracting the predicted level of pollution, including scale effects and movements along the EEC, from the scale effect alone (in column (2)). Offsets due to demographic changes are calculated in an analogous manner. Offsets due to shifts in the EEC are calculated as the residual, and the offsets in columns (4), (6), and (8) sum to column (3) by construction. Figures in columns (4) through (9) are based on EECs estimated in tables 2 and 3.

Figure 1. Pollution Embodied in Household Consumption – PM10



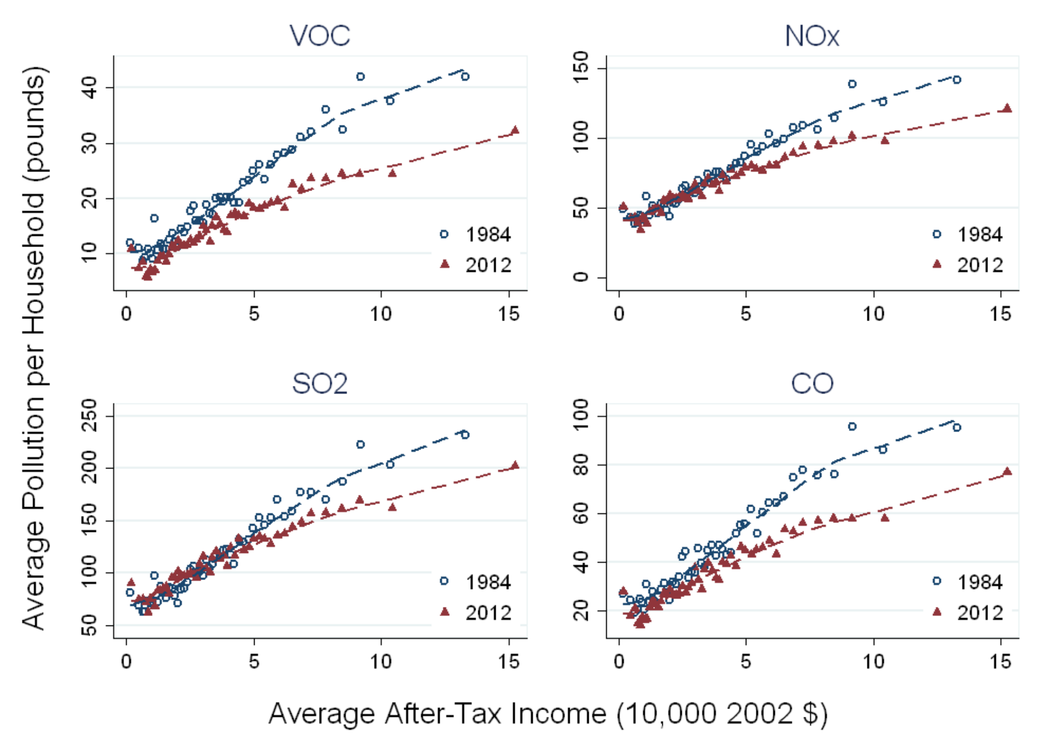
Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2 percent of the 1984 CEX sample, with the highest and lowest one percent of households trimmed based on after-tax income. The top income bin includes all remaining households with real annual after-tax income higher than $110,529.

Figure 2. EECs Based on Pre-Tax Income – PM10



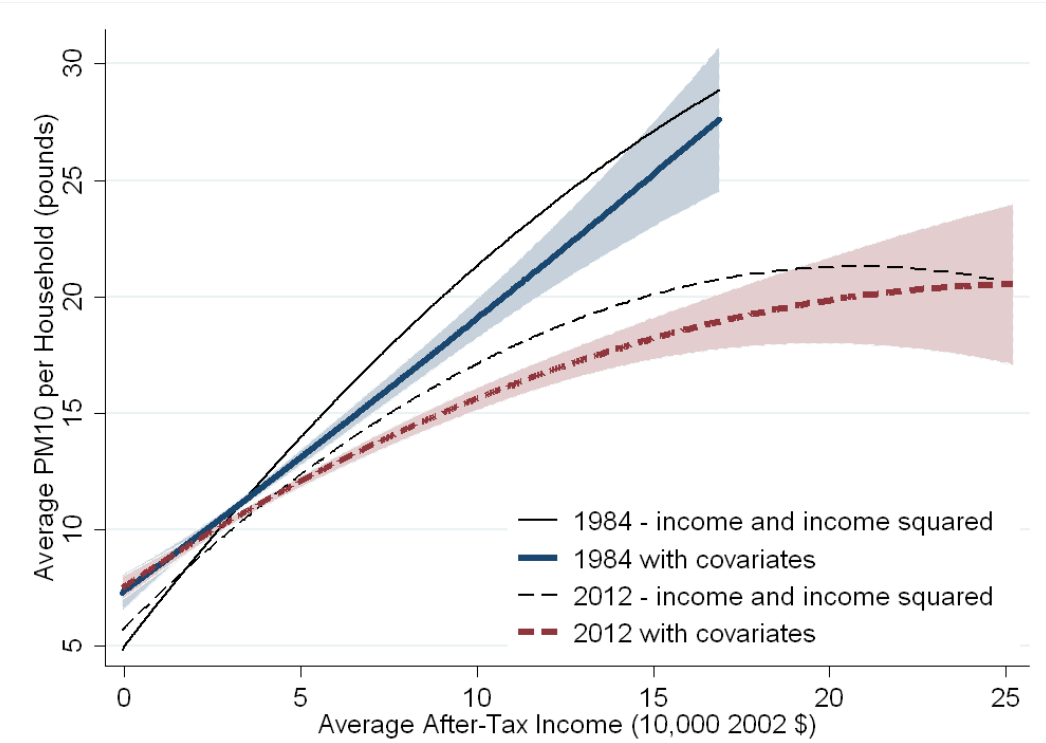
See notes to figure 1.

Figure 3. Nonparametric EECs for Other Pollutants



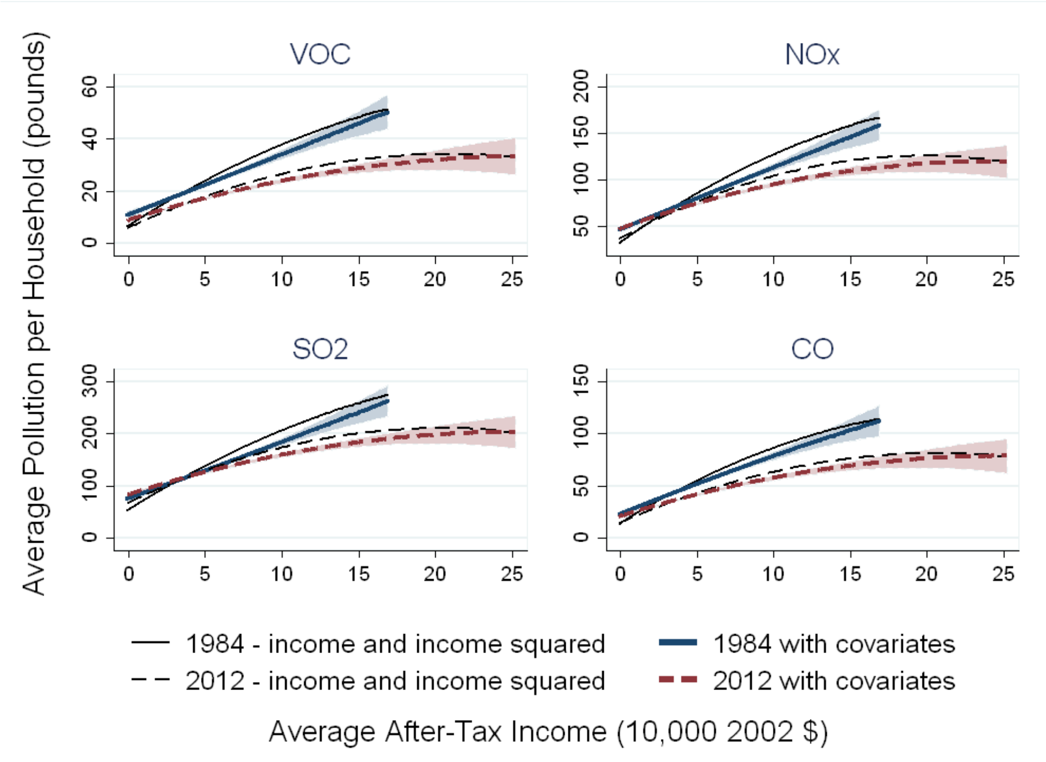
See notes to figure 1.

Figure 4. EECs Based on Parametric Estimates – PM10



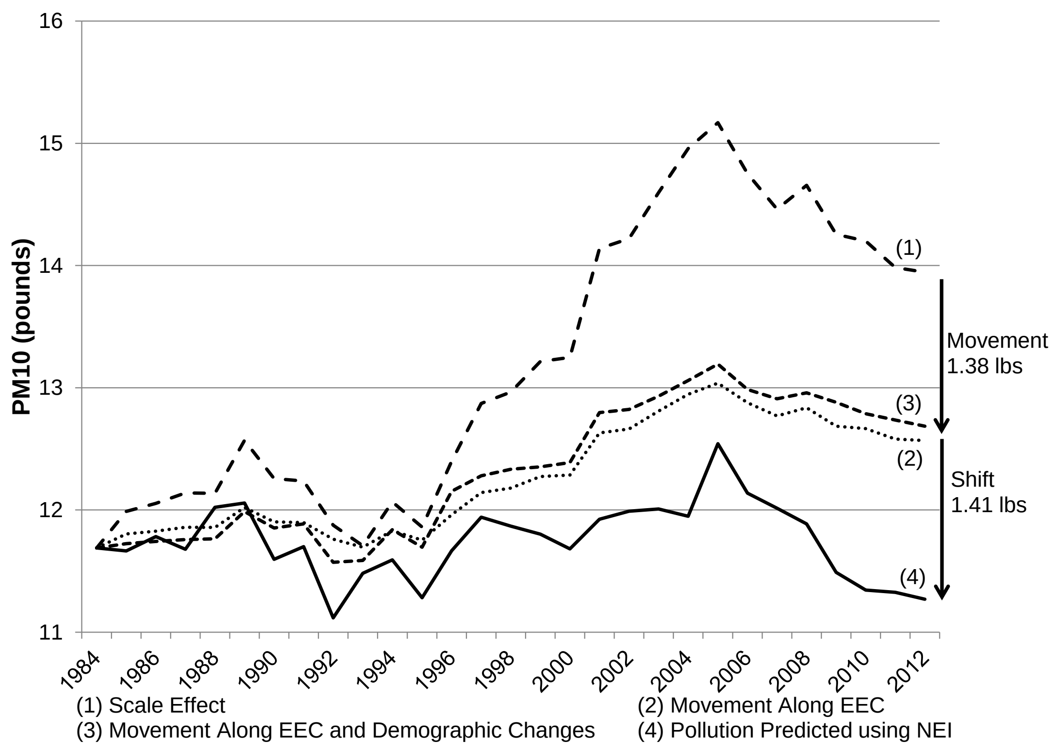
All other covariates are fixed at their mean values. Inflation adjustments as in figure 1. Standard errors for pollution intensity of production are not estimated, so 95 percent confidence intervals (shaded) reflect variation in household spending.

Figure 5. EECs for Other Pollutants Based on Parametric Estimates



See notes to figure 4.

Figure 6. Decomposition of Predicted Pollution from Household Consumption



Notes: The scale effect is calculated by increasing pollution in proportion to real after-tax income growth. Movements along and shifts in the EEC are calculated by estimating pollution in each year using the 1984 EEC coefficients. Pollution predicted using NEI-based pollution coefficients is estimated by matching itemized consumption expenditure in each year with the corresponding industry's 2002 pollution intensity.