Integrating Heterogeneity into Benefit-Cost Analysis[1]

Richard L. Revesz,[*] Burçin Ünel[**] & Sarah Wheaton[***]

Generally, benefit-cost analyses are conducted based on impacts on an average member of the population—that is, a person with median characteristics. Often, however, the populations affected by government policies vary from the median in significant ways. Heterogeneity by age, race, income, and other factors is relevant to the assessment of the benefits and costs of particular policies. On the benefits side, certain groups face higher levels of exposure to environmental harms and, where the dose-response functions are non-linear or where exposure to different pollutants results in synergistic harms, these groups face higher harms from exposure to an additional unit of pollution than does an average member of the population. Also, certain groups have higher vulnerability per unit of exposure to particular exposures. And, on the cost side, certain groups bear higher burdens because of differences in geography, spending patterns, and other behaviors. This Article provides a robust review of the scientific, epidemiological, and economic literature for each of these mechanisms, surveys what agencies have already done, and sets forth an agenda for future research.

The consideration of the distribution of costs and benefits of policies can lead to large differences in the assessment of benefits and costs. As a result, a benefit-cost analysis based on impact to the average member of the population would significantly underestimate the benefits of regulatory protections, both because the actually affected population may be at higher risk and because these high outliers raise the overall population risk.

INTRODUCTION

Every president since Ronald Reagan has required benefit-cost analysis of significant regulatory proposals to economically justify regulatory or deregulatory actions. Typically, this analysis is based on the impact, in dollars, of a policy on an average member of the population, multiplied by the number of affected individuals (Robinson et al., 2016; Cranor & Finkel, 2018). How this impact is distributed among the population is generally viewed as an additional inquiry, but not an integral part of the benefit-cost analysis. Importantly, analyses that inquire about differential impacts, such as distributional or environmental justice analysis, are typically more contested, and subject to significant changes from one administration to another even when there is continued commitment to benefit-cost analysis.

For example, the Biden Administration updated the Circular A-4 to highlight the importance of including a separate distributional analysis alongside the benefit-cost analysis in the RIA. But during the first weeks of his second term, President Donald Trump reversed the update, and revoked executive orders on environmental justice issued by Presidents Bill Clinton and Joe Biden, which were focused on identifying populations suffering from disproportionate

---

[1] This paper is a condensed version of "The Myth of Evenhanded Administration: Integrating Individual Heterogeneity into Benefit-Cost Analysis," which is forthcoming in the *Duke Law Journal*.

[*] AnBryce Professor of Law and Dean Emeritus, New York University School of Law; Administrator, White House Office of Information and Regulatory Affairs (January 3, 2023 to January 20, 2025).

[**] Research and Policy Director, Institute for Policy Integrity at New York University School of Law.

[***] J.D. Candidate, 2027, New York University School of Law.

environmental and health burdens and taking actions to address those effects (Exec. Order 14,215, 2025). These reversals happened even though President Trump reaffirmed the Executive Branch's commitment to subjecting regulations to benefit-cost analysis, embodied in Executive Order 12,866. A subsequent memorandum by the Acting Administrator of the White House Office of Information and Regulatory Affairs—the institution that reviews proposed and final rules to determine whether they comply with this order—underscored the importance of rigorous benefit-cost analysis in evaluating regulatory initiatives (OMB, 2025).

But both of these approaches miss a key analytical detail: an accurate benefit-cost analysis for a government policy simply cannot be done without knowing the distribution of harms that the policy would address, and if and how there are populations that are disproportionately affected. In the environmental policy context, for example, ignoring how the impacts of harms differ across the population is likely to underestimate the benefits of pollution reduction, in some cases by a large amount. This discrepancy occurs because benefit-cost analysis is traditionally based on the impact, in dollars, of a policy on a median member of the population multiplied by the number of affected individuals (Cranor & Finkel, 2018; Finkel, 2014; Robinson, Hammitt, & Zeckhauser, 2016). Since the risk distribution is typically right-skewed—meaning there are more individuals with very high risk than very low risk—a benefit-cost analysis using this method will markedly underestimate the cumulative risk across the population (Stensrud & Valberg, 2017).[2]

This Article moves forward the academic discussion of the relationship between benefit-cost analysis and distributional impacts to a new phase. At the beginning, the dominant view was that concerns about distributional impacts were extraneous to benefit-cost analysis, as any undesirable consequences in the distributional impacts could be corrected by other means, particularly the tax-and-transfer system (Revesz, 2018). Currently, the benefit-cost analysis is considered mostly as an economic efficiency inquiry, while a distributional analysis is an equity-based inquiry alongside the results of a benefit-cost analysis (Revesz & Yi, 2022; Revesz & Ünel, 2023). This paper establishes that the distribution of costs and benefits is an essential input to the benefit-cost analysis itself, not just an afterthought relevant only to the question of how to deal with a policy that maximizes net benefits but has undesirable distributional features. To explain the importance of taking into account the underlying heterogeneity in costs and benefits in benefit-cost analysis, we use the context of environmental regulations as an example. But our core insight about the centrality of understanding the distribution of costs and benefits to the efficiency of regulations applies to regulations in all domains.

For environmental regulations, the heterogeneity can arise because there are differences in exposure or vulnerability, both of which would affect the estimate of the benefits of a given regulation. There could also be heterogeneity about the cost incidence of the regulation. In this paper, we (1) comprehensively lay out the mechanisms through which heterogeneity is relevant to these assessments in environmental regulations, drawing heavily on literature from chemistry, medicine, and economics; (2) show, through an extensive review of the empirical literature, that

[2] A numerical example illustrates the issue and explains why it can drive the policy choice. Assume that 90 people in a population suffer a harm of 10 each and 10 people suffer a harm of 100 each. The median (or "average") person in the population therefore suffers a harm of 10. If the benefit-cost analysis is done on the basis of the harm of that person and then multiplied by the whole population, the total harm would be estimated as 1,000 (10 times 100). But the total harm is in fact 1,900 (10 times 100 plus 90 times 10). Assume that the costs are 1,500. When the benefits are computed correctly the benefits of 1900 exceed these costs and the policy can be justified under Exec. Order 12,866. But when the benefits are computed by reference to a median or average person the benefits are estimated to be only 1,000 and do not justify the costs.

the failure to account for this heterogeneity is likely to lead to a significant undervaluation of the benefits of regulation; and (3) connect these failures to actual regulatory benefit-cost analysis as carried out by EPA, particularly underscoring developments from the Biden and Trump Administrations. Its two key insights are that benefit-cost analysis is likely to underestimate population risk without taking this heterogeneity into account and that risks are correlated with key demographic characteristics in a way that makes demographic consideration a critical element of benefit-cost analysis.

The discussion proceeds as follows. Part I examines the state of the empirical literature on differential levels of exposure and of the consequences of such nonuniformity. Part II does the same for differential levels of vulnerability. Both these discussions are relevant to the determination of the benefits of environmental regulation, even though the insights here can apply to different regulatory contexts as well. Part III turns its attention to the cost side, underscoring the importance of determining the distribution of the costs in a well-conducted benefit-cost analysis. While the empirical evidence on differential impacts is fairly robust, further research is needed before benefit-cost analysis can fully account for the impact of differences in vulnerability, exposure, and costs. Part IV focuses on these gaps.

I. EXPOSURE

Individuals differ in their level of exposure to environmental harms. Exposure differences can come through a variety of channels, including proximity, duration, and timing (Sexton & Hattis, 2007). And, research shows that average exposure to a range of environmental hazards, including pollution (Jbaily et al., 2021; Collins et al., 2016), heat (Hsu et al., 2021; Hoffman et al., 2020; Locke et al., 2021), and contaminated water (Martinez-Morata et al., 2022) differs across racial and income groups. But except for a few specific cases (DeAngeli et al., 2024), exposure in regulatory impact analyses is generally calculated by reference to an average individual in an age group (U.S. Env't Prot. Agency, 2011), ignoring potential racial or socioeconomic heterogeneity. This Part shows that the resulting estimates can understate the benefits of regulation, in some cases significantly.

There are two main reasons why understanding the heterogeneity in exposure is important for the accuracy of benefit-cost analysis. First, these variations mean that the baseline exposure levels (that is, the exposure levels without any policy changes) might vary among different populations. A different starting point would alter the magnitude of the change in risk if the relation between exposure and risk is non-linear (for example, when the harm caused by an additional unit of pollution is greater when the baseline exposure is higher). Thus, using the baseline estimated for an average individual would lead to inaccurate impact estimates in cases of non-linearity.

Second, when individuals are exposed to more than one chemical or to a single chemical in combination with non-chemical stressors, the combined effects may be greater than the additive effect of each individual stressor. These combinations are particularly relevant for disadvantaged communities, as they often face exposure to a wider variety of chemical sources (Cushing et al., 2015) and to more non-chemical stressors (National Research Council, 2004) than the average member of the population. If the negative effects are more than additive, ignoring the variations in exposure may systematically underestimate environmental benefits if disadvantaged individuals are affected.

This Part lays out the mechanisms for variations in exposure. Section A looks at the mechanisms behind variation in standard and nonstandard exposure pathways. Section B discusses the importance of these differences for a benefit-cost analysis through non-linear dose-response functions for single exposures and the effect of cumulative exposures.

A. Mechanisms for Differential Exposure

1. Variations in Typical Exposure Pathways

A basic understanding of why exposure levels could differ across populations is important for correctly carrying out benefit-cost analyses. In a typical exposure pathway, a pollutant is emitted or discharged at the source location. It may then dissipate, mix, or change chemical form and travel using a transport medium such as air or water to the points of exposure—usually assumed to be an individual's residence or workplace. For instance, a pollutant could be emitted by a factory and transported through the air to residents living near the factory. These standard pathways are generally better understood and used in agency analyses (Burger & Gochfeld, 2011).

These standard exposure pathways can differ significantly across the population. For instance, one study found a forty-five-fold difference in toxic exposure between the most and least-exposed census tracts (Alvarez et al., 2022). If damages are not a linear function of exposure, failing to consider these differences will underestimate the population benefits of regulation. Since exposure is bounded at zero, the presence of these highly exposed individuals likely means the total population exposure is higher than exposure of the average individual multiplied by the population size.

Because the exposure of any particular individual can be difficult to observe directly (Farber, 2024), considering demographics may help determine which areas have highly-exposed individuals. Demographic exposure variation could occur for a number of reasons, including individual sorting (i.e., disadvantaged individuals moving towards sources of pollution), firm sorting (i.e., polluting firms moving to disadvantaged areas), and weak compliance and enforcement in disadvantaged areas. As a result, disadvantaged populations might be concentrated in areas with higher pollution exposure. We explain each of these explanations briefly below.

a. Residential sorting

There is empirical evidence for both when individuals move away from environmental harms to avoid exposure ("fleeing the nuisance") and when environmental harms decrease home values, attracting price-sensitive individuals to move in ("coming to the nuisance"). Low-income, minority, low-education, and renter families are more likely to move into high hazard areas, such as flood zones (Bakkensen & Ma, 2020; Wolverton, 2009) or areas near a power plant (Davis, 2011; Been, 1994). High-income, white residents are also more likely to move away from these areas (Pais et al., 2013). Finding data and estimating these movement patterns, which take place over decades, remain a challenge for regulatory agencies.

b. Firm sorting and low bargaining power

A related but distinct issue is firm sorting. For reasons such as low bargaining power or labor costs, polluting firms may choose to locate in disadvantaged areas. Literature shows firms with toxic outputs are more likely to initially locate in areas with higher shares of non-white residents. Those firms also attract similar firms through agglomeration effects, increasing total emissions in those areas and decreasing the probability of firm closure (De Silva et al., 2016). Another study found similar results for educated areas, noting that firms with toxic outputs were more likely to relocate away from areas with higher population density and more educated residents than from other areas (Wang et al., 2021). A third study showed additional empirical evidence for low bargaining power, finding that linguistically isolated, low-education, and low-income households negotiated less favorable lease terms in natural gas siting contracts, leading to more long-run violations (Timmins & Vissing, 2022). One countervailing dynamic in this literature is that disadvantage in an area can have the opposite effect, deterring firm entry due to labor or security concerns (Wolverton, 2023). However, the weight of the evidence seems to suggest disproportionate toxic siting in disadvantaged areas.

c. Inconsistent compliance and enforcement

Disadvantaged areas also face higher exposure due to uneven compliance with regulations or enforcement for violations. Multiple studies find that state and local governments perform fewer environmental enforcement actions in low income, high-poverty areas as well as those with large immigrant populations (Konisky, 2009; Konisky & Schario, 2010; Spina, 2015). A lack of enforcement resources can also lead to longer periods of noncompliance. For instance, one study found that communities with the longest periods of noncompliance with the Safe Drinking Water Act had higher shares of racial, ethnic, and linguistic minorities (Fedinick et al., 2019).

2. Variations in Nonstandard Exposure Pathways

In addition to these standard exposure pathways, economic and social behavior of different groups might lead to "unique" exposure pathways that disproportionately affect disadvantaged groups. A pathway becomes "nonstandard" if any of the steps in a typical pathway deviates from the norms described above. Nonstandard pathways could be a result of a variety of factors such as age, income, or social behaviors. For example, exposure pathways might become nonstandard due to unusual methods of exposure or carrying out standard activities at higher rates than those of an average individual (Burger & Gochfeld, 2011).

As an example, children are often placed on the floor or outdoor surfaces, which can increase their exposure to dust, tracked-in soil, chemicals from synthetic carpets, or pesticides (U.S. Env't Prot. Agency, 2011; Moya et al., 2004). Additionally, childhood behaviors such as pica (eating dirt), hand-to-mouth-behavior, and frequent touching of surrounding objects can increase exposure (U.S. Environmental Protection Agency [EPA], 2011; Moya et al., 2004). Children under six months of age consume over five times as much tap water per unit of body weight compared to adults (Moya et al., 2004), leading to higher rates of food or water-born toxicants in children than their adult counterparts (Sly & Flack, 2008; EPA, 2011).

Nonstandard pathways also occur as a result of variations in social or economic behavior. For example, some racial, ethnic, or socioeconomic groups have high use of products, such as cosmetics (Burger & Gochfeld, 2011), medicinal remedies (Sly & Flack, 2008), scented products (Fandiño-Del-Rio et al., 2024), and low-quality furniture (Adamkiewicz et al., 2011), which can lead to increased chemical exposures. Another example of nonstandard exposure comes from fish consumption. Consumption of self-caught fish forms the single largest human exposure to chemicals, particularly mercury (Burger & Gochfeld, 2011). Survey evidence has found high levels of self-caught fish consumption among low-income individuals and those with less than a high school education (Burger & Gochfeld, 2011). These high levels of consumption can lead to mercury exposure, which is a particular issue among subsistence fishers in tribal communities (EPA, 2023).

Substandard occupational safety and housing might also contribute to nonstandard exposure pathways. Workers in occupations with regular chemical exposures, such as those in agriculture, chemical manufacturing, logging, and construction face high chemical exposures (Kalweit et al., 2020) which can be brought home to family members on clothing (Hyland & Laribi, 2017). Low-income individuals are often overrepresented in these high-exposure positions, which can be temporary, seasonal, or lack bargaining power and other workplace protections (Hyland & Laribi, 2017). Similarly, poor housing conditions among the socioeconomically disadvantaged can lead to high levels of exposure. Data from the American Housing Survey shows that families with low socioeconomic status live in smaller homes with greater occupant density, lower air filtration rates, peeling paint, structural issues, and water leaks (Adamkiewicz et al., 2011). These difficulties, which are often associated with older and poorly-maintained housing, can lead to elevated exposures through many channels, including lead poisoning (Vivier et al., 2011), cockroach allergen exposure (Sarpong, 2005), secondhand smoke exposure, and mold (Adamkiewicz et al., 2011).

EPA has considered certain unique exposure pathways for a long time. The agency has published child-specific exposure factors since 2008 (EPA, 2008) and its main Exposure Factors Handbook includes a chapter on fish intake with sections specifically focusing on Native populations (EPA, 2011). In the Biden Administration, two innovative rules began to consider demographic differences in occupational exposures (DeAngeli et al., 2024). However, absent these specific considerations, exposure is generally calculated based on the impact on an average individual in an age group, ignoring potential racial or socioeconomic heterogeneity (EPA, 2011).

This practice may in part be due to data challenges. Unique pathways affect isolated or groups of individuals, who may be hard for surveyors to access or may not be able to produce estimates with sufficient statistical power (Burger & Gochfeld, 2011). A related but distinct concern arises when individuals are not isolated but are spread evenly across a large population, such as in the case of unique product consumption. It may be difficult to identify relevant individuals in these situations, particularly when many consumer studies are based on unreliable individual recall (Burger & Gochfeld, 2011).

B. Relevance to Benefit-Cost Analysis

This Section explains why understanding the underlying heterogeneity in exposure is important for an accurate benefit-cost analysis.

1. Non-Linear Dose Response Functions

Understanding the dose-response functions is the first step in understanding why disproportionate exposure is relevant to benefit-cost analysis. In performing benefit-cost analysis, EPA and other agencies must convert exposure (“dose”) into units of harm (“response”). To do so, they use a dose-response function, which mathematically converts units of exposure into units of harm.

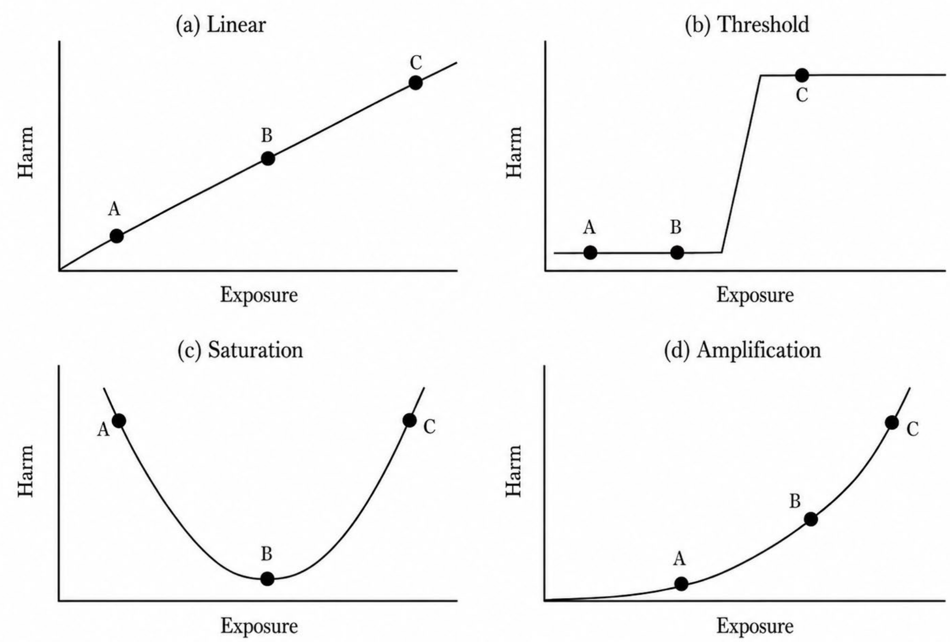
EPA generally uses two types of dose-response models. For cancer endpoints, it uses a linear dose-response function, in which the cancer risk increases at a constant rate with any increase in exposure, shown in Figure 1a (Varshavsky et al., 2023). The baseline level of exposure is thus not important for understanding the additional harm from a given exposure increase.

For non-cancer endpoints, EPA uses a non-linear, threshold model (EPA, 2008). This model "assumes a threshold below which exposures have no quantifiable risk" (McGartland et al., 2017) either due to scientific uncertainty or because physiological systems can ward off effects at low exposure levels (Nielsen et al., 2023). As shown in Figure 1b, EPA typically multiplies the threshold level by a given factor (usually 10) (Varshavsky et al., 2023) to account for uncertainty and then assumes little or no risk below that level (EPA, 2025). Unlike in a linear model, the same change in exposure can create vastly different harms depending on whether an individual is above or below the threshold.

But evidence suggests the true dose-response relationship can have many other shapes. Empirical evidence shows a saturation relationship (e.g., Figure 1c) between temperature and various harms, with benefits to temperature increases at cold temperatures but large harms from increases at high temperatures for endpoints including mortality (Deschênes et al., 2011), crop yields (Schlenker & Roberts, 2009), labor hours (Zivin & Neidell, 2014), and economic productivity (Burke et al., 2015). Amplification relationships, shown in Figure 1d, occur when marginal damages increase with high levels of exposure. Empirical evidence shows that there may be an amplification relationship between, for example, air pollution and economic activity (Dechezleprêtre et al., 2019).

Figure 1 illustrates why it is critical to understand baseline exposure, changes in exposure, and the relevant dose-response shape in order to accurately account for benefits of environmental regulation. Unless all relationships follow Figure 1a, ignoring heterogeneity in exposure will underestimate the harm avoided for population exposure.

Figure 1. Illustrative Dose-Response Curves



Alt text: A set of four line graphs, each showing a different dose-response curve. Panel (a) is a straight line, where the "harm" (y-axis) at the point marked C is greater than B is greater than A.

Panel (b) is a line graph that starts horizontal for points A and B, becomes a steep vertical, then levels out for a higher level of harm for point C. Panel (c) is u-shaped, with A and C at the same level of harm and B much lower. And panel (d) is a J-shape, with point C above B above A.

The first Trump Administration started to reevaluate EPA's dose-response functions, with a 2018 proposed rule suggesting EPA evaluate a range of dose-response assumptions, "including assumptions of a linear, no threshold dose-response" (EPA, 2018). After many critical comments, particularly from those worried about movement towards a threshold model for cancer endpoints, the provision was removed from the 2021 final rule (EPA, 2021a), which was rescinded by the Biden Administration (EPA, 2021b). The Biden Administration focused on differentiating dose-response functions by race, but not on altering their shape (EPA, 2024).

2. Cumulative Impacts

In addition to potential non-linear effects of a single chemical, there is a growing body of research showing the interactive effects of multiple chemical exposures as well as the impact of non-chemical stressors. As a default, EPA generally assumes chemical independence, meaning each chemical an individual is exposed to impacts the body separately from other chemicals (National Research Council, 2009). However, some chemicals may be synergistic, meaning they interact in a way that makes their combined impact stronger than each individual impact (Sexton & Hattis, 2007). Researchers have found synergistic effects across a range of chemicals, including estrogenic agents (Silva et al., 2002), steroids (Thrupp et al., 2018), and common air pollutants (Kuehn, 1996). These interactive effects may occur in around five percent of chemicals, creating millions of potential interactive pairs (Thrupp et al., 2018). The differences in magnitude can also be quite substantial; one review study found mixtures with four to one hundred times their expected additive impacts in animals (Martin et al., 2021). If individuals are exposed to hundreds or thousands of chemicals every day, these interactive effects could be quite significant. Not taking these interactions into account would thus underestimate the benefits of eliminating some or all of these exposures.

A second body of work looks at the cumulative effects of chemical and non-chemical stressors. Recent research also suggests an interaction between pollutants and psychological stressors. Yet, data and methodological challenges remain due to confounding factors for epidemiologic research, as social stressors and pollutant exposure are often correlated (Martin et al., 2021). Thus, more research is needed to understand specific causal pathways for how stress and socioeconomic stressors affect health and susceptibility.

Although cumulative exposure is the area that has perhaps received the most attention in the risk evaluation space, as well as from the EPA as evidenced by reports dating back to 1986, there are many remaining challenges. Data limitations affect both chemical and non-chemical analysis, as it is nearly impossible to model every possible mixture, and little appropriate, aggregated data exists on individual-level non-chemical stressors (Payne-Sturges et al., 2018; EPA, 2023). There are also mathematical challenges, with disagreements over which models best represent the combined effects of multiple exposures (Payne-Sturges et al., 2021). Additionally, there is a lack of understanding of the mechanisms behind interactive effects, leading to questions about the rigorousness of the work in light of confounding variables and reverse causality issues (Clougherty et al., 2014; Padula et al., 2020). Robust cumulative exposure analysis also requires analysis of background and historical exposure, and the temporal element adds additional data and conceptual complications (Sexton & Hattis, 2007). The combination of these factors can make cumulative exposure exponentially complicated, with the National Research Council's 2009 Science and Decisions Report emphasizing the need for a streamlined, well-articulated, carefully-considered process if cumulative risks are to be considered properly.

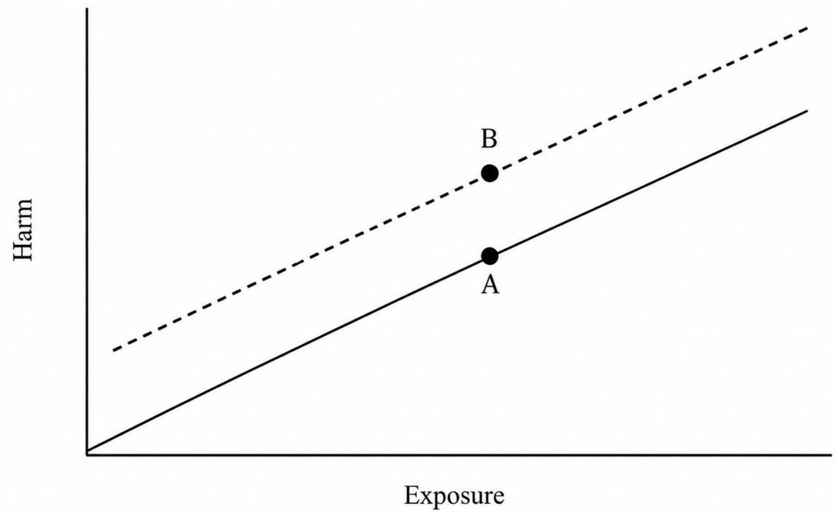
II. VULNERABILITY

Even at the same level of exposure, individuals can suffer differing levels of risk or harm due to differences in underlying vulnerability. Indeed, studies have found empirically large differences in vulnerability across individuals, with the same exposure causing tens or hundreds of times the harm to some highly affected individuals compared to the average (Kuehn, 1996; Decisions, 2017; Varshavsky et al., 2023). These differences are not limited to extreme cases. One study notes that the top five percent of the population may be at twenty-five times more risk of cancer than the average person and the top one percent may be at one hundred times the risk (Kuehn, 1996).

The risk distribution for environmental harms is typically right-skewed, meaning that there are more individuals with very high risk than very low risk. Since total benefits are calculated by multiplying the risk to an average individual by the size of the population, ignoring these high outliers will markedly underestimate the total population risk. This effect is present even if the pollution is uniformly distributed across the population, though it is exacerbated when an affected group has higher-than-average exposure. When the underlying risk distribution is as such, using an average dose-response function based on average vulnerability would lead to inaccurate estimates, underestimating population risk by ignoring the outsized effect of these high outliers. An accurate analysis would instead require using different dose-response functions for different groups.

Figure 2 illustrates the importance of vulnerability in benefit-cost analysis. Assume that regulators believe that affected individuals fall on the lower dose-response curve but, instead, they actually fall on the higher one because of their increased vulnerability. For a given exposure level, the regulator will estimate the harms avoided at point A when they are actually at the higher point B. Even if the dose-response functions have the same shape, the estimation of harm at any given level will be too low.

Figure 2. Shifted Linear Dose-Response



Alt text Line graph with a straight dashed line above a straight solid line. The lower, solid line has a point "A" and the higher, dashed line has a point "B" at the same exposure level (x-axis), but "A" shows higher harm (y-axis).

In most cases, it is impossible to observe these exact levels of risk for each individual. However, as discussed previously, the presence of these high outliers means that the total population risk is higher than the risk to an average individual multiplied by the number of affected individuals. Additionally, as this Part discusses, research suggests vulnerability is not evenly distributed across demographic groups. A large and growing literature shows that disadvantaged groups face larger harms even when exposed to the same level of an environmental bad (Chay & Greenstone, 2003; Josey et al., 2023; Wang et al., 2017). Therefore, knowing about socioeconomic, racial, or ethnic status can help regulators determine how the total population benefits differ from those determined by reference to an average individual.

A range of factors contribute to these differences in vulnerability. Age and presence of other health conditions are common factors in determining how vulnerable an individual is. In addition, other factors such as access to medical care, ability to make defensive expenditures, genetics, and ability to consumption smooth after negative events play a role. This Part reviews the literature on each mechanism, exploring the state of the literature, remaining challenges, and existing applications throughout the government.

A. Age

Individuals face increased vulnerability at certain ages. Children have higher susceptibility to environmental harms for a range of reasons, including increased absorption of environmental toxins, immaturity of key detoxifying enzymes, underdevelopment of the blood-brain barrier, and later development of key organs including the skin, lungs, kidneys, and the immune system (Wang et al., 2017). Risks are higher during specific "developmental windows of susceptibility," such as for in utero or premature infants (Bhatia et al., 1996), children under the age of two (Sly & Flack, 2008), and pubescent children (Ginsberg et al., 2005). Children also face greater total harms due to their longer life expectancy, which can allow long-latency diseases more time to develop and creates a greater number of years of disability (Sly & Flack, 2008).

The elderly are also at greater risk than average. As organ systems age, they become less able to clear harmful chemicals. For instance, decreased liver and kidney function in the elderly leads to higher retention of harmful substances (Ginsberg et al., 2005). Higher rates of underlying health problems, such as low bone density and decreased respiratory function, may also magnify the impacts of substances such as fluoride or smoke which harm those systems (Risher et al., 2010). These mechanisms have been shown to increase the harmful effects of pollution, with the relationship between particulate exposure and mortality being stronger among elderly populations.

Current regulatory frameworks consider age more than most other demographic characteristics. This consideration dates back to President Clinton's 1997 Executive Order on environmental health in children and the launch of EPA's Office on Children's Health Protection (Exec. Order 13,045, 1997; EPA, 2025). These institutional investments have led to rules considering the share of affected children and occasionally of elderly people in the Obama, first Trump, and Biden Administrations (DeAngeli et al., 2024; Cecot et al., 2026).

However, often these issues come up in terms of differential exposure or information about risk, not differential impact or vulnerability (DeAngeli et al., 2024). Federally, chemical risk factors are set based largely on data for healthy adults (Varshavsky et al., 2023). Researchers have suggested calculating separate risk factors for vulnerable groups (e.g., having separate allowable levels for different age groups) or decreasing allowable risk based on vulnerable groups (e.g., setting the allowable risk for everyone based on the most at-risk group), an approach already adopted by states such as California (Varshavsky et al., 2023) and in the National Ambient Air Quality Standards (EPA 2025a).

B. Health Conditions

Preexisting health conditions are another source of vulnerability. For instance, pregnant people are more vulnerable to pollutants due to physiological adaptations (Koman, 2018) and pregnancy-specific disease risk (Koman, 2018). Total damages from pollution in pregnancy are also higher because there are adverse health outcomes for both parents and fetuses, which can lead to poor health outcomes at birth and into later life (Di Renzo et al., 2015). Other health conditions show similar effects. For instance, a study by Wang and coauthors showed that the association between particulate exposure and mortality was higher for those with previous hospitalizations for a range of diseases, including diabetes, myocardial infarction, COPD, or congestive heart failure (Wang et al., 2017). Pollution exposure also contributes to asthma symptoms and increased mortality among asthma patients (Liu et al., 2019). And aflatoxin was shown to be a stronger carcinogen among those with Hepatitis B (Wu-Williams et al., 1992).

Since less than half the population is affected by these conditions, multiplying the damage to an average person by the size of the affected population will entirely miss the effects of these high outliers. In addition, affected areas with a higher-than-average prevalence of these conditions may show even larger effects. In cases where disease prevalence is unobservable, demographics may provide some information about these elevated risks. For example, racial and ethnic minorities have an elevated rate of many chronic diseases (Price et al., 2013). Therefore, if an affected area has a larger-than-average share of racial minorities, population vulnerability may be higher.

For chronic diseases, the Climate and Environmental Justice Screening Tool, used as part of the Justice40 Initiative, compiled data showing which geographic locations had high rates of high-risk health conditions (Price et al., 2013). However, it is not clear that EPA has considered these health conditions when thinking about susceptibility in regulatory impact analyses. Accordingly, current benefit-cost analysis might underestimate risk, both for the population as a whole and for policies affecting groups with high prevalence of these conditions.

C. Healthcare Access and Quality

Another source of vulnerability is differential access to high-quality healthcare. Exposure to environmental stressors can cause a range of health risks, but those risks can often be managed with appropriate health care. While it is difficult to directly quantify healthcare quality, correlational evidence suggests that many of these health problems, such as high blood pressure (Fiscella & Sanders, 2016), cancer (Haque et al., 2021), and asthma (U.S. Department of Health and Human Services [HHS], 2025) are less well-controlled or show higher mortality rates among low-income and racial minority populations, often many multiples. This evidence could suggest that populations without access to quality healthcare suffer larger-than-average environmental harms.

On the access side, Black, Hispanic, low-income, and rural populations have the lowest health insurance rates (Mahajan et al., 2021; Lee & Porell, 2020). Black and low-income neighborhoods also have difficulty attracting health care providers, especially high-quality providers (Bailey, 2017). These barriers to access, combined with others such as inadequate transportation and lack of child care, have real impacts on health care access for individuals in disadvantaged communities (Rios et al., 1993). Research has shown that these access issues make disadvantaged individuals less likely to seek care at all and make it more likely that they seek care when a disease is at a more advanced stage (Rios et al., 1993). Disadvantaged individuals, especially the uninsured, are also less likely to receive cancer screenings (Fiscella & Sanders, 2016; Sosa et al., 2021; Rustagi et al., 2022; Liss & Baker, 2014). These differences in access mean that after the same exposure, disadvantaged individuals are less likely to receive timely, appropriate treatment, leading to worse outcomes (Probst, 2011).

Disadvantaged communities also have lower health care quality. Quality may be lower across a variety of dimensions, including hospital quality scores and mortality rates (Fiscella & Sanders, 2016), likelihood of following clinical treatment guidelines (Rios, 1993), and likelihood of seeing a board-certified physician (Bach et al., 2004). These quality differences result in differing treatment. For instance, one study found Black lung cancer patients had lower incidence of high-cost treatments like chemotherapy and immunotherapy, while Black, Hispanic, low-income, and publicly-insured patients were likely to forego or delay cancer surgery (Dwyer et al., 2023). Therefore, even if patients are able to access health care, evidence suggests the treatment might still end in worse outcomes due to poor quality.

Despite the rich literature on socioeconomic and racial health disparities, there is relatively little literature linking these differences to increased environmental harms. The closest the research comes is through noting that there is a stronger relationship between particular exposure and negative health outcomes in areas with weak healthcare access or high poverty than in other areas (Wang et al., 2017; Cakmak et al., 2011; Josey et al., 2023). However, other than a single paper that at least posits that $PM_{2.5}$ health outcomes may be affected by poor healthcare access in the South (Kioumourtzoglou et al., 2016), most of the literature simply hypothesizes healthcare access as a possible avenue without giving any causal evidence about the relationship between healthcare access and environmental harms.

Beyond the challenge of sorting out many possible causal factors, the literature also faces challenges with confounding variables. In particular, papers often use high healthcare spending or utilization as a proxy for quality, which is difficult to observe directly. However, the opposite can also be true. High health spending or utilization, especially in emergency settings, is associated with poor health (Patel et al., 2016). Utilization may also increase in areas with high pollution (Barwick et al., 2026). Both of these issues may mask access or quality problems in disadvantaged communities.

EPA has discussed these issues, though with limited application in its Regulatory Impact Analyses. The 2023 EJ Technical Guidance lists "[a]ccess to health care (e.g., interaction with health care providers and resources; lack of preventative care and deferred treatment)" as a contributor to differential vulnerability that should be considered (EPA, 2023). Some Biden-era rules, such as the updated Particulate Matter NAAQS, have shown how uninsured populations may face different absolute exposure and changes in exposure under alternate scenarios (DeAngeli et al., 2024). However, these analyses have usually looked only at differences in exposure levels, not how the same change in exposure might have a different impact on vulnerable groups (EPA, 2024).

D. Defensive Expenditures

Another reason why some groups may be more vulnerable to environmental harms is differential ability to invest in mitigatory expenditures. If certain individuals or groups are less able to invest in measures to protect against environmental harm, a policy reducing pollution may produce larger benefits for them. The presence of these individuals alone may increase population harm. The literature also suggests that areas with high numbers of disadvantaged and low-education individuals may suffer even greater harms.

There is a broad economics literature on this topic, as observed willingness to pay for mitigatory measures can serve as a proxy for willingness to pay for non-market climate goods such as clean air or cool temperatures. For instance, if one person were willing to pay $50 for a pollution filtering face mask and another was not, economists could infer that one person values the corresponding exposure reduction at $50 or more while the other person values it less (Barwick et al., 2026). With enough observations, economists can determine how much society values goods that cannot be bought or sold on the market (Bell et al., 2009; Graff Zivin et al., 2009; Graff Zivin & Neidell, 2009; Deschênes & Greenstone, 2011; Dickie & Gerking, 1992).

In recent years, this literature has been critiqued on the grounds that behavior does not necessarily reflect individual preferences. In a landmark work, a paper by Greenstone and Jack noted reasons why an individual's ability to pay for these goods may not reflect their true preferences. Most obviously, low-income individuals may lack the resources to invest in these goods at their preferred level, and hence traditional WTP could suggest values different by orders of magnitude (Greenstone & Jack, 2015). Greenstone and Jack describe this issue by noting that the marginal utility of investment in necessities may be higher than the marginal utility of environmental goods at low income levels (Greenstone & Jack, 2015). For that reason, low-income individuals may choose to invest in food and medicine instead of air filters or other protective goods. This difference is most fully empirically fleshed out through the literature on air conditioning. Central air conditioning is less prevalent among low income and other socially disadvantaged groups (Medina-Ramoón et al., 2006; Scott et al., 2025; O'Neill et al., 2005; Salvo, 2020). High temperatures are also more correlated with negative health outcomes among these groups, with one study finding that a lack of air conditioning was a main contributor. Income may be a constraint for a variety of other defensive investments, including acquiring non-contaminated water (Kremer et al., 2011), and air purifiers (Ito & Zhang, 2020). Even if all individuals make some investments, high-income individuals may make the most expensive and effective investments, such as using air purifiers instead of face masks (Sun et al., 2017).

Defensive investments may also vary by education level. While there is little U.S. research on the topic, international studies show that individuals may under-invest in defensive measures due to lack of information about risk (Graff Zivin & Neidell, 2009; Neidell, 2010), and understanding of risk may be higher for more educated individuals (Khanna et al., 2025). The relationship between education and mitigation has been shown across multiple investments. For instance, one study by Jalan and Somanathan found that a one-year increase in education level for a household's most educated adult increases the probability of home water purification by between 1.5 and 2 percent in rural India (Jalan et al., 2009). Another defensive response that may be affected by education is migration from more- to less-polluted areas. One study found that migration responses from more- to less-polluted areas in China were almost entirely caused by young, educated workers (Khanna et al., 2025).

Finally, some types of desired mitigatory behaviors, such as moving neighborhoods, may be more difficult if racial discrimination is at play. For instance, a study by Christensen, Sarmiento-Barbieri, and Timmins found that discriminatory behavior against Black residents was a barrier to potential moves to low-pollution neighborhoods (Christensen et al., 2022). Another study by Depro, Timmins, and O'Neil found a similar trend when comparing Hispanic and white residents (Depro et al., 2015).

Each of these mechanisms suggests that it is important to understand inter-individual heterogeneity in defensive expenditures. Whether it be through income constraints, education and information, or racial discrimination channels, disadvantaged individuals invest less in mitigatory measures than average individuals. Therefore, the same pollution reduction would have a larger impact on those groups if they are less able to protect themselves at existing levels.

This literature still has room for growth on several dimensions. Until recently, research on defensive expenditures was largely concentrated in affluent communities (Greenstone & Jack, 2015; Dickie & Gerking, 1992). When studies did look at less privileged areas, they usually stopped at the conclusion that adoption and willingness to pay were low with little effort to dig into the mechanisms of why (Jayachandran, 2022). Evidence in this area is improving, particularly with emerging empirical evidence from China's War on Pollution (Greenstone et al., 2021). However, in order for it to be useful in a regulatory context, research needs to move beyond using defensive expenditures as a proxy for willingness to pay, instead thinking about how existing differences might mean that already-protected individuals have lower benefits from environmental regulation while less-protected individuals would have larger benefits. This work is still in its early stages, with a few papers suggesting marginal damages may be lower in high-pollution areas when certain types of defensive expenditures are made (Hsiang & Narita, 2012; Barreca et al., 2016; Hornbeck & Keskin, 2014). However, these studies are largely retrospective and do not seek to predict future impacts of mitigation.

E. Genetics

Genetic variation explains some differences in susceptibility. Recent research has found a number of genetic mutations that heighten the relationship between pollution exposure and health outcomes, either through increasing the probability of developing a pollution-triggered disease after exposure, such as asthma, or through decreasing the body's ability to clear harmful chemicals that cause diseases like cancer. Specific genes affecting the impact of pollution include those affecting clearing of toxins, carcinogen metabolism (National Research Council, 1994), inflammatory response (Motsinger-Reif et al., 2024), and DNA repair rates (National Research Council, 1994). In other cases, the specific mechanisms are less clear, but specific genes have been linked to the connection between air quality and diseases such as asthma (Castro-Giner et al., 2009; Yeatts et al., 2006) and cardiac disease (Chahine et al., 2007; Park et al., 2006; Ward-Caviness, 2019).

These genetic variations are important for two reasons. First, some of these genes increase susceptibility to environmental harm by factors of ten or more times (Varshavsky et al., 2023). Even if they are spread evenly across the population, their presence creates high outliers, making the total population risk higher than the risk for an average individual multiplied by the number of affected individuals. Second, if the affected population contains a higher-than-average concentration of these genetic markers, the population risk may be even higher, making it more important that the benefit-cost analysis incorporates this heterogeneity. Without taking these differences into account, the estimated benefits of environmental regulation would be inaccurately low (CDC, 2024).

While currently research provides a useful starting point, some challenges remain. First, genetic studies have historically been done mostly of individuals of European descent, making it difficult to document differences across race, class, or other demographic groups (Motsinger-Reif et al., 2024). Second, it can be difficult to disentangle the impacts of genetic and environmental impacts. For instance, Black communities may both have higher frequencies of certain genes and live in areas with higher pollution. Creative methodology and statistical design are needed to disentangle these possible drivers (Johansson et al., 2019). Third, the human genome is large and complex, making target-gene studies extremely time, resource, and statistically intensive and often inconclusive (Motsinger-Reif et al., 2024). Finally, while advances in big data could be immensely helpful, ethical researchers must also incorporate ethical and data privacy concerns (Motsinger-Reif et al., 2024).

These advances have rarely been discussed by EPA or other government regulators. EPA's 2023 Updated Environmental Justice Guidance asks regulators to consider differential population vulnerability, including "biologic factors" such as genetics (EPA, 2023). However, to date, these factors have not been incorporated into any Regulatory Impact Analyses.

F. Consumption Smoothing

Finally, increased vulnerability may come from the inability to respond to a negative shock. Individuals affected by negative environmental outcomes may lose money for a range of reasons, including job loss, medical bills, or needing to rebuild infrastructure. In the short run, the lack of a wealth "buffer" for disadvantaged households may lead to larger harms from decreased consumption or from an inability to spend on health or infrastructure (Farber, 2023). In the long run, these economic shocks can lead to decreased investment in nutrition, health, and education, decreasing future earning potential (Hill et al., 2024). These issues, which may be worse for low-income and minority populations, can increase the magnitude and types of damages faced in the current generation and pass them on to future generations.

These types of secondary impacts are difficult to observe causally. As observed in a paper by DeAngeli et al., evaluating indirect impacts, behavioral changes, and categories of costs and benefits beyond direct health and cost benefits are areas EPA and other regulators rarely touch and could improve (DeAngeli et al., 2024).

III. Regulatory Costs

Executive Order 12,866 mandates that agencies consider *net* benefits, which is the difference between the benefits and costs of a regulation. While the preceding discussion has focused on heterogeneity of the benefits of a regulation, there is also heterogeneity in the incidence of costs. Understanding this heterogeneity is important for the accuracy of the benefit-cost analysis and thus for the efficiency of regulations. If an agency estimates costs based on an average individual but the actual costs are higher because of the characteristics of the group affected by the regulation, the agency will underestimate costs and overestimate net benefits, potentially leading to over-regulation. This effect can somewhat counteract the potential underestimation of benefits discussed in Parts I and II.

In practice, looking at heterogeneity on the cost side is rare. According to DeAngeli et al., of the sixty-eight significant EPA rules issued between 2012 and 2024, only three considered the distribution of costs (DeAngeli et al., 2024). Another study, looking at a longer time span and larger variety of agencies, found that only thirteen percent of rules considered the incidence of costs quantitatively and thirty percent considered them at all, compared to well over half that considered the distribution of benefits (Cecot et al., 2026).

There are two possible reasons for this sparsity of analysis. First, analyzing how the regulatory costs are distributed can be technically challenging and resource intensive. While regulatory costs initially affect regulated firms, some proportion are passed on to consumers, employees, or shareholders. Correctly modelling this pass-through is technically challenging, time intensive, and data intensive, especially at a granular level (EPA, 2023). And second, EPA itself has been agnostic about the practice. The 2023 EJ guidelines note that cost analysis "will not substantially alter the assessment" in cases where costs are evenly distributed across the population and does not push for a cost analysis in most or all cases.

While EPA does not always consider the distribution of costs, the 2023 guidelines give a list of situations where additional cost analysis may be warranted such as when the regulatory action represents a higher proportion of income for certain populations, there are differences on ability to adapt or substitute goods, or differences in behavioral responses that affect the incidence of costs. In this Part, we survey the literature on some of these areas, including price effects, transition costs, and environmental gentrification. Because the literature in this area is less developed, we consider a broad range of possible costs, most of which have not yet been operationalized in EPA analysis.

A. Price Effects

One of the main mechanisms leading to heterogeneity on the cost side is differential price impacts. Environmental regulations can lead to price changes for energy or energy-intensive goods. These price changes can affect groups differently, either because those populations spend a higher proportion of their income on affected products or because upstream economic effects are more likely to reach certain types of consumers.

Energy regulations may be regressive if low-income households spend a larger proportion of their income on energy. The economics literature indeed finds low-income households spend larger shares of their income on energy (Pizer & Sexton, 2019). This relationship may also hold true for other groups, such as Black households (Carley & Konisky, 2020; Rausch et al., 2011) and households in certain parts of the country (Rausch et al., 2011; Mathur & Morris, 2014; Fullerton & Heutel, 2010). A final important point is that although there are differences in spending between demographic groups, an emerging literature emphasizes that within-group variations are also large, emphasizing the need for more granular individual and group analyses (Pizer & Sexton, 2019; Cronin et al., 2019).

However, understanding the distributional impacts becomes more complicated when price changes do not directly and completely pass through to consumers. Environmental regulations initially increase costs to producers, who may need to invest in more expensive capital or different inputs. Those changes are at least partially passed on to consumers through higher prices; the degree to which input costs reach consumer prices is known as pass-through. The literature does suggest that in some cases, the pass-through rate to consumers is close to one hundred percent (Ganapati et al., 2020; Kotchen, 2021; Bento & Jacobsen, 2007), although it can vary considerably depending on timeframe (Miller et al., 2017; Bento & Jacobsen, 2007) and competitiveness of an industry (Muehlegger & Sweeney, 2022), ultimately depending on the relative elasticities of supply and demand (Drupp et al., 2021). Alternatively, environmental regulations may affect the valuation of companies in affected industries, passing through equity prices and causing income losses for owners and shareholders (Bushnell et al., 2013).

These pass-through rates are relevant for two reasons. First, regulations affecting industries or areas with higher pass-through rates are likely to have different distributional consequences, as the owners of businesses are systematically different than consumers (Edelberg & Steinmetz-Silber, 2024). Second, in an even more targeted way, pass-through rates may be different for different types of consumers. For instance, low-income consumers might simply decrease consumption of a more-expensive good instead of paying increased prices (Stolper, 2024; West & Williams, 2004; Bruegge et al., 2019; Doremus et al., 2022). In other cases, high-income households are better able to adapt by purchasing efficient appliances or vehicles (Levinson, 2019). There also may be differences along other dimensions; for instance, one study found higher pass-through in rural areas where it was not possible to change driving behavior or switch to different fuel providers (Harju et al., 2022). Considering these behavioral and pass-through differences makes regulations look significantly less regressive than looking at spending shares alone (West & Williams, 2004).

While these differences in consumption are often the most observable source of cost incidence, there are several remaining challenges. First, measures of income and consumption are imperfect, with point-in-time income failing to capture large lifetime fluctuations and consumption failing to capture differential savings patterns across groups (Pizer & Sexton, 2019; Hassett et al., 2009). Second, measuring pass-through and accounting for behavioral changes require the use of complicated, multi-sector models, all of which require assumptions and have their own benefits and drawbacks (EPA, 2024). Especially when measuring these costs dynamically, the analysis can be data intensive and require assumptions about inputs ranging from discounting and technological change to how homeownership or consumption patterns might shift. Many of these effects can also counteract each other, making final incidences sensitive to modelling assumptions.

B. Transition Costs

A second set of costs from an environmental regulation are transition costs, or the costs borne by communities that are directly affected by the regulation. The industries most likely to be affected by environmental regulations, notably fossil fuel production and carbon-intensive manufacturing, are heavily regionally concentrated (Raimi et al., 2022; Hanson 2023). Employment losses are the clearest and most widely studied transition cost (Carley & Konisky, 2020; Blonz et al., 2023). If a regulation makes it more expensive to produce, firms may move away from production, reducing the need for labor in the area. If workers in an area are unable to retrain or move or if a community lacks the infrastructure to attract new industries, areas suffer large job losses (Castellanos et al., 2023; CEA, 2022).

These losses have been shown empirically. One early study found that Clean Air Act nonattainment counties—that is, counties not meeting the National Ambient Air Quality Standards of the Clean Air Act—lost 590,000 jobs compared to attainment counties in the fifteen years following enactment (Greenstone, 2002). And while economy-wide employment impacts can appear small, another study found that a $45 per ton carbon tax would increase the unemployment rate by large amounts in affected industries and countries (Castellanos & Heutel, 2023). These employment losses are not limited to only polluting industry, however. Multiple studies have found effects on other industries as well, as regional demand for other goods and services declines (Carley & Konisky, 2020; Du & Karolyi, 2023). The resulting losses in earnings can be long-lasting, with one estimate finding average earnings declines of five percent for the first three years after the Clean Air Act, with earnings starting to recover only five years later (Walker, 2013). It is worth noting, however, that regulation may also lead to green job creation, leaving the total employment effect ambiguous (Institute for Policy Integrity, 2017).

Understanding heterogeneity is important in estimating costs because communities affected by the regulation might be demographically dissimilar from the population as a whole (though they are also more likely to enjoy the benefits of environmental regulation). Carbon-intensive communities are more likely to be disadvantaged on a range of metrics, including poverty, unemployment, educational attainment, local infrastructure, and poor health outcomes (Shrestha & Saha, 2023; CEA, 2022; Carley & Konisky, 2020). Therefore, policies forcing reforms to carbon-intensive industry will likely cause larger employment losses for disadvantaged individuals. Even within affected communities, empirical literature suggests low-skill workers (Intriago et al., 2020), young and inexperienced workers (Curtis, 2017), older workers (Curtis et al., 2024), less-educated workers (Curtis et al., 2024), and men (Yip, 2018) are more likely to be affected. Additionally, communities with fewer outside employment options—likely those suffering economic distress—also face larger employment losses (Walker, 2013). Therefore, understanding the distribution of costs on actual communities and individuals affected and taking the heterogeneity of costs into account may lead to different aggregate cost estimates than simply using estimates based on an average individual.

A related challenge is to understand the impact of the regulation on the economy, which requires using economy-wide, general equilibrium analysis in order to adequately capture potential intersectoral effects (Hafstead & Williams, 2020). For instance, what appears to be large employment declines in the coal industry could be larger economy-wide due to declines in downstream or service industries, or smaller due to movement into clean sectors. Another difficulty comes from modelling search frictions or the idea that the skills and preferences of affected workers may prevent them from immediately finding another job (Hafstead & Williams, 2020). Finally, a number of studies have data only at the industry or job-level, making it difficult to find detailed information about demographics.

EPA currently models employment impacts at the economy-wide and industry level using a Computable General Equilibrium (CGE) model. As far as we are aware, they have not modelled transition costs for any rules in the Biden Administration or earlier (EPA, 2025b).

C. Housing Prices and Environmental Gentrification

Another consequence of increasing environmental quality is environmental gentrification. The phenomenon occurs when, in short, "high-income households bid up housing prices by their own willingness to pay [after environmental improvements], and if that willingness to pay exceeds that of the poor, the perverse result is that cleaning up pollution in a poor neighborhood can harm the poor, as prices increase by more than their willingness to pay" (Banzhaf et al., 2019).

The theory of environmental gentrification contains within it three separate predictions. The first is that environmental improvements increase housing prices. This phenomenon has been observed empirically both for home values (Haninger et al., 2017; Sager & Singer, 2025) and rents (Grainger, 2012), although the increase may be larger and more direct for homeowners (Bento et al., 2015; Grainger, 2012; Tra, 2010). These changes affect renters and owners differently, with owners benefitting directly from appreciating home prices while renters pay higher prices without benefitting from appreciation. The second prediction is that these changes affect disadvantaged communities disproportionately. While it is the case that disadvantaged individuals are likely to live in initially polluted areas, and are more likely to be renters (U.S. Department of the Treasury, 2025), increasing home values in these areas may also disproportionately benefit low-income residents (Cassidy et al., 2025). It is worth noting that even absent migration impacts, these two predictions on their own could cause differing costs across groups. Regardless of their migration decisions, disadvantaged renters living near newly cleaned up sites may face higher than average costs through increased rents.

However, the third prediction in the environmental gentrification literature is that these changes in housing prices will cause individuals to move, re-arranging those who benefit from the cleanup. The lack of granular, individual-level migration and pollution data make this phenomenon difficult to observe directly. One study found that while the Clean Air Act decreased pollution the most for the initially disadvantaged, later years saw benefits going to initially advantaged residents (Voorheis, 2017). Another study found that Superfund cleanup was associated with increased population density and in-migration of educated and wealthy individuals (Gamper-Rabindran et al., 2011). A few large sorting models have also found increasing migration (Binner & Day, 2018; Sieg et al., 2004), although results have overall been mixed (Basu et al., 2025; Greenstone & Gallagher, 2008). Because this migration decreases the benefits that would otherwise accrue to disadvantaged individuals, it is empirically similar to a cost.

Looking at the relationship between environmental regulation and residential sorting is ripe for additional research, in part because data limitations are especially notable. For instance, observing migration patterns can require extremely fine geographic data, with migration outcomes varying across miles or even blocks (Gamper-Rabindran & Timmins, 2013; Depro et al., 2015). These questions are also best answered using longitudinal data about individual exposure, demographics, and migration patterns, which has rarely been available (Voorheis, 2017). These data limitations also lead to a number of modelling challenges. Studies looking at aggregate demographic change may miss the true migration relationship unless they adequately compare to control sites, account for changing provision of other public goods, and know about who exactly is making moves (Banzhaf et al., 2019). A final, conceptual challenge is that economists might consider these changes to be "efficient" given the underlying distribution of resources, perversely drawing into question the need for environmental regulation at all (Banzhaf et al., 2019).

EPA has published research on housing price changes, including an entire section of its *2010 Handbook on the Benefits, Costs, and Impacts of Land Cleanup and Reuse* devoted to research on environmental gentrification (EPA, 2010). The 2023 EJ Technical Guidance also described situations where "costs are concentrated on some types of households (e.g., renters) more than others" as areas where additional cost incidence analysis may be warranted. However, it is not clear that this modelling has actually made it into any of its current rules.

IV. Remaining Data and Research Gaps

As the preceding discussion shows, understanding the underlying distribution of benefits and costs of a regulation is key to a well-conducted benefit-cost analysis. Yet there are analytical challenges that agencies face in addressing heterogeneity in their analysis, whether it is by age, income, demographic group, or any other factor. In this Part, we summarize these challenges, laying out a priority agenda for researchers.

A. Gaps in Data

A key gap in understanding the heterogeneity of costs and benefits is the availability of data at a granular scale. There is a lack of available or reliable data for certain subgroups. For example, it is not always possible to break down exposure or vulnerabilities by income, age, or race and ethnicity (DeAngeli et al., 2024). Similarly, if the exposure happens by a unique, nonstandard exposure pathway, agencies might not have the necessary data to understand exposure and risk by subgroup (Burger & Gochfeld, 2011). Further, granular analysis, especially for cumulative impacts analysis, requires temporally and spatially granular data by subgroup, which is often unavailable even when data is available at an aggregate level. As a result, agencies are limited in their ability to understand both the baseline distributions of risks and exposure, and any potential heterogeneity in the incremental effects of a regulation.

As we discussed above, understanding cumulative impacts is also important for accurately estimating the benefits of a regulation. Yet, important data gaps about interactions of multiple chemical and non-chemical stressors at a granular scale make it difficult for agencies to understand the underlying heterogeneity in impacts. Some of these gaps are a result of lack of consensus on how cumulative impacts should be calculated (e.g., how to handle joint impacts of multiple pollutants, policies, covered and noncovered sources, and historical exposure), which other pollutants or stressors could be important to include in the cumulative impact analysis (e.g., physical non-chemical exposure, psychological stress, poverty, mental health measures, historical land use and siting), or which metrics should be used to measure these other factors.

But, even when there is consensus on the importance of a factor, data challenges remain, as some of these factors require very fine geographic data (e.g., a few blocks can have large effects in dense urban environments). This problem is even more challenging for taking into account residential sorting and demographic changes in long-run analyses, which is difficult to forecast at an aggregate level.

While these challenges have existed during previous administrations, recent policy changes by the Trump Administration, such as their decision not to collect emissions data from many polluters, significantly exacerbated them (Joselow, 2025). As a result, it is important that the research community increases the efforts to collect and maintain data sources and make them publicly available.

B. Gaps in Empirical Evidence

Quantifying and monetizing effects of a proposed policy requires causal empirical evidence on the policy's effect. Understanding the underlying heterogeneity of these effects requires further causal estimates at a granular level, disaggregated by subgroups. But such detailed analysis is usually lacking in the academic literature.

One of the main reasons for this gap is confounding variables, making it methodologically challenging to distinguish between correlation and causation, especially in the epidemiological literature. For example, robustly showing that psychological stressors worsen the impact of pollution requires controlling for all other factors that might be directly causing psychological stress and worsening pollution impact (e.g., income). When this analysis cannot be done in a high-quality manner, and researchers miss or omit such confounding variables in their analysis, the empirical evidence cannot be used to credibly estimate causal impacts of a regulation.

Empirical evidence on certain effects, especially on the cost side, is also lacking. The empirical literature on differential cost pass-throughs and transition costs is sparse and speculative, even at an aggregate level. While understanding some of these effects require time and resource intensive general equilibrium modeling, understanding how costs of regulations are distributed among groups would be important for evidence-based policymaking, especially given the current Administration's emphasis on affordability and reducing costs for all Americans. Without understanding the incidence of costs, it is not possible to understand whether the current deregulatory policies of the Trump Administration are achieving their goals of reducing costs on specific businesses or groups.

C. Gaps in Understanding Underlying Mechanisms

When the underlying mechanisms for translating impacts into consequences are not well understood, different effects might be working in opposite directions, hiding the true magnitude of each effect. For instance, disadvantaged communities may both attract polluting businesses due to low costs and repel them due to crime or poor infrastructure. Without understanding these underlying mechanisms, it is hard to predict what the ultimate impact of a particular policy will be.

Alternatively, there could be multiple underlying causes for the same mechanism, which would complicate the estimation of the benefits of the regulation. For instance, increasing average income in a newly cleaned up area could indicate either that advantaged individuals are gentrifying the area or that disadvantaged individuals are willingly leaving to pursue cheaper options. Or different observed harms by subgroup could come from either different baseline exposure and a non-linear dose-response function or from different underlying vulnerability.

Without a clear understanding of these underlying mechanisms, it is challenging for agencies to include such effects, let alone their distributions, in their regulatory analyses. In addition, these mechanisms are important to understand the relationship between exposure and risk, and of the true shapes of the dose-response curves. Thus, more research in this area is needed.

D. Gaps in Theoretical Understanding

Finally, there are important theoretical gaps. For example, there is still a lack of consensus on how research conceptualizes and measures very low and very high levels of risk that do not scale well from averages (Cranor & Finkel, 2018). Without this understanding, it is difficult to estimate accurate dose-response functions. Work in this area would be especially important for toxic pollutants, where many of the risks remain unquantified and unmonetized (Sinden, 2019).

Another important theoretical gap is about how to treat uncertainty in benefit-cost analysis. Different disciplines approach uncertainty differently, with a different threshold of when an effect should be included in regulatory analyses. Economic theory might support reducing risk even if there is uncertainty, while public health researchers might lean toward including only effects they consider as reasonably certain. Given that it is more likely that a granular analysis by group is going to be more statistically noisy and thus more uncertain than an aggregate analysis, resolving how to treat uncertainty is a key step in incorporating heterogeneity into regulatory analysis.

This question is especially relevant under the Trump Administration, which recently started not including in benefit-cost analyses effects it deems too "uncertain." (Joselow, 2026) Thus, developing a unifying interdisciplinary framework to value health risks in benefit-cost under conditions of uncertainty and more thinking on how agencies should account for such uncertainty is increasingly important.

CONCLUSION

This Article provides the blueprint for what the next generation efforts to account for heterogeneity in the distribution of costs and benefits in a regulatory impact analysis should look like. In particular, using environmental regulations as an example, it shows that basing benefit-cost analyses on the impacts on average individuals is likely to lead to incorrect results, particularly by significantly underestimating the benefits of pollution reduction.

There are multiple reasons for this potential misestimation. Overall, exposure levels could vary based on where populations live, where they work, and their type of employment, among other social, economic, and policy factors. Without knowing which mechanisms are at play for a given pollutant and thus which groups are more likely affected by that mechanism, it is impossible to properly translate changes in pollution exposure to changes in risk, and thus accurately calculate the benefits of a given regulation (or costs of deregulation). For example, a regulation reducing chemical exposure at a workplace might affect a completely different population than a regulation reducing the same chemical exposure at the same level in a residential setting. As a result, these two regulations, even if they reduce the same chemical by the same amount, would lead to different benefits. Similarly, if the dose-response function is non-linear or if there are cumulative impacts, the same level of pollution reduction might lead to different levels of benefits in different groups.

In addition, there are multiple reasons why certain members of the population may be more vulnerable to environmental harms. Without considering these factors, either alone or as they correlate with observable demographic characteristics, a benefit-cost analysis will mis-estimate the benefits of a regulation, likely underestimating these benefits. Thus, understanding the underlying heterogeneity is critical to assessing the total net benefits and efficiency of the regulation.

Similarly, while EPA rarely looks at the incidence of regulatory costs, such accounting is necessary to accurately represent net benefits for affected groups. The literature is less coherent and developed in this area, but there are multiple mechanisms for heterogeneity in cost incidence: uneven price pass-through, transition costs, and impacts from migration. Integrating these second-order impacts is technically complex, and methodological improvements are needed in order to rigorously calculate net benefits, particularly for regulations that might disproportionately impose costs on specific groups.

While there has been significant progress in data collection and methodology in recent decades to understand such heterogeneity in costs and benefits, many gaps remain in addressing and incorporating them in regulatory analyses. Noting and starting to address these gaps is essential to improve efficiency of regulations in the future.

References

Adamkiewicz, G., Zota, A. R., Fabian, M. P., Chahine, T., Julien, R., Spengler, J. D., & Levy, J. I. (2011). Moving environmental justice indoors: understanding structural influences on residential exposure patterns in low-income communities. *American Journal of Public Health*, *101*(S1), S238–S245.

Alvarez, C. H., Colosanti, A., Evans, C. R., & Ard, K. (2022). Intersectional inequalities in industrial air toxics exposure in the United States. *Health & Place*, *77*, 102886.

Bach, P. B., Pham, H. H., Schrag, D., Tate, R. C., & Hargraves, J. L. (2004). Primary care physicians who treat blacks and whites. *New England Journal of Medicine*, *351*(6), 575–584.

Bailey, Z. D., Krieger, N., Agénor, M., Graves, J., Linos, N., & Bassett, M. T. (2017). Structural racism and health inequities in the USA: Evidence and interventions. *The Lancet*, *389*(10077), 1453–1463.

Bakkensen, L. A., & Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, *104*, 102362.

Banzhaf, S., Ma, L., & Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, *33*(1), 185 –208.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, *124*(1), 105–159.

Barwick, P. J., Li, S., Rao, D., & Zahur, N. B. (2026). The health care cost of air pollution: Evidence from the world's largest payment network. *Review of Economics and Statistics*, *108*(1), 110–128.

Basu, S., Ketcham, J. D., & Kuminoff, N. V. (2025). Environmental regulation, residential sorting, and pollution exposure among senior Americans. Journal of Environmental Economics and Management, 103211.

Been, V. (1994). Locally undesirable land uses in minority neighborhoods: Disproportionate siting or market dynamics? *Yale Law Journal, 103(6),* 1383–1422.

Bell, M. L., Ebisu, K., Peng, R. D., & Dominici, F. (2009). Adverse health effects of particulate air pollution: Modification by air conditioning. *Epidemiology*, *20*(5), 682–686.

Bento, A., Freedman, M., & Lang, C. (2015). Who benefits from environmental regulation? Evidence from the Clean Air Act amendments. *Review of Economics and Statistics*, *97*(3), 610–622.

Bento, A., & Jacobsen, M. (2007). Ricardian rents, environmental policy and the "double-dividend" hypothesis. *Journal of Environmental Economics and Management*, *53*(1), 17–31.

Bhatia, S.,. Robison, L. L., Oberlin, O., Greenberg, M., Bunn, G., Fossati-Bellani, F. & Meadows, A. (1996). Breast cancer and other second neoplasms after childhood

Hodgkin's disease. *New England Journal of Medicine*, *334*(12), 745–751.Binner, A., & Day, B. (2018). How property markets determine welfare outcomes: An equilibrium sorting model analysis of local environmental interventions. *Environmental and Resource Economics*, *69*(4), 733-761.

Blonz, J., Tran, B. R., & Troland, E. E. (2023). *The canary in the coal decline: Appalachian household finance and the transition from fossil fuels* (NBER Working Paper No. 31072). National Bureau of Economic Research.

Boyle, K. J. (2017). Contingent valuation in practice. In P. A. Champ, K. J. Boyle, & T. C. Brown (Eds.), *The economics of non-market goods and resources* (2nd ed., pp. 83–131). Springer.

Bruegge, C., Deryugina, T., & Myers, E. (2019). The distributional effects of building energy codes. *Journal of the Association of Environmental and Resource Economists*, *6*(S1), S95–S127.

Burger, J., & Gochfeld, M. (2011). Conceptual environmental justice model for evaluating chemical pathways of exposure in low-income, minority, Native American, and other unique exposure populations. *American Journal of Public Health*, *101*(S1), S64–S73.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239.

Bushnell, J. B., Chong, H., & Mansur, E. T. (2013). Profiting from regulation: Evidence from the European carbon market. *American Economic Journal: Economic Policy*, *5*(4), 78–106.

Cakmak, S., Dales, R. E., Rubio, M. A., & Blanco Vidal, C. (2011). The risk of dying on days of higher air pollution among the socially disadvantaged elderly. *Environmental Research*, *111*(3), 388–393.

Carley, S., & Konisky, D. M. (2020). The justice and equity implications of the clean energy transition. *Nature Energy*, *5*(8), 569-577.

Cassidy, A. W., Hill, E. L., & Ma, L. (2025). *Who benefits from hazardous waste cleanups? Evidence from the housing market* (NBER Working Paper No. 30661). National Bureau of Economic Research.

Castellanos, K., & Heutel, G. (2023). Unemployment, labor mobility, and climate policy. *Journal of the Association of Environmental and Resource Economists*, *11*(1), 3–40.

Castro-Giner, F., Künzli, N., Jacquemin, B., Forsberg, B., de Cid, R., Sunyer, J., Jarvis, D., Briggs, D., Vienneau, D., Norback, D., Gonzalez, J. R., Guerra, S., Janson, C., Antó, J., Wjst, M., Heinrich, J., Estivill, X., & Kogevinas, M. (2009). Traffic-related air pollution, oxidative stress genes, and asthma (ECHRS). *Environmental Health Perspectives*, *117*(12), 1919–1924.Cecot, C., Hahn, R. W., & Imamoglu, E. (2026). How well do governments assess the distributional impacts of policy? *Regulation & Governance, 0*, 1–11.

Chahine, T., Baccarelli, A., Litonjua, A., Wright, R. O., Suh, H., Gold, D. R., Sparrow, D., Vokonas, P., & Schwartz, J. (2007). Particulate air pollution, oxidative stress genes, and heart rate variability in an elderly cohort. *Environmental Health Perspectives*, *115*(11), 1617–1622.Chay, K. Y., & Greenstone, M. (2003). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *The Quarterly Journal of Economics*, *118*(3), 1121–1167.

Christensen, P., Sarmiento-Barbieri, I., & Timmins, C. (2022). Housing discrimination and the toxics exposure gap in the United States: Evidence from the rental market. *Review of Economics and Statistics*, *104*(4), 807–822.

Clougherty, J. E., Shmool, J. L., & Kubzansky, L. D. (2014). The role of non-chemical stressors in mediating socioeconomic susceptibility to environmental chemicals. *Current Environmental Health Reports*, *1*(4), 302–313.

Collins, M. R., Muñoz, I., & JaJa, J. (2016). Linking "toxic outliers" to environmental justice communities. *Environmental Research Letters*, *11*(1), 015004.

Cranor, C. F., & Finkel, A. M. (2018). Toward the usable recognition of individual benefits and costs in regulatory analysis and governance. *Regulation & Governance*, *12*(1), 131–149.

Cronin, J. A., Fullerton, D., & Sexton, S. (2019). Vertical and horizontal redistributions from a carbon tax and rebate. *Journal of the Association of Environmental and Resource Economists*, *6*(S1), S169–S208.

Curtis, E. M. (2017). Who loses under cap-and-trade programs? The labor market effects of the NO_x Budget Trading Program. *Review of Economics and Statistics*, *100*(1), 151–166.

Curtis, E. M., O'Kane, L., & Park, R. J. (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. *Environment and Energy Policy and Economics*, *5(1)*, 127–160.

Cushing, L., Faust, J., August, L. M., Cendak, R., Wieland, W., & Alexeeff, G. (2015). Racial/ethnic disparities in cumulative environmental health impacts in California: Evidence from a statewide environmental justice screening tool (CalEnviroScreen 1.1). *American Journal of Public Health*, *105*(11), 2341–2348.

Davis, L. W. (2011). The effect of power plants on local housing values and rents. *Review of Economics and Statistics*, *93*(4), 1391–1402.

DeAngeli, E., Morgenstern, R., Ünel, B., & Wolverton, A. (2024). *Consideration of environmental justice in EPA's regulatory analyses: A review and assessment* (Working Paper 24-22). Resources for the Future.

Dechezleprêtre, A., Rivers, N., & Stadler, B. (2019). *The economic cost of air pollution: Evidence from Europe (OECD Economics Department Working Paper No. 1584)*. Organisation for Economic Co-operation and Development.

Depro, B., Timmins, C., & O'Neil, M. (2015). White flight and coming to the nuisance: Can residential mobility explain environmental injustice? *Journal of the Association of Environmental and Resource Economists, 2*(4), 439–468.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the U.S. *American Economic Journal: Applied Economics*, *3*(4), 152–185.

De Silva, D. G., Hubbard, T. P., & Schiller, A. R. (2016). Entry and exit patterns of "Toxic" firms. *American Journal of Agricultural Economics, 98*(3), 881–909.

Di Renzo, G. C., Conry, J. A., Blake, J., DeFrancesco, M. S., DeNicola, N., Martin, J. N., Jr., McCue, K., Richmond, D., Shah, A., Sutton, P., Woodruff, T.J., Ziemin van der Poel, S., & Giudice, L. C. (2015). International Federation of Gynecology and Obstetrics opinion on reproductive health impacts of exposure to toxic environmental chemicals. *International Journal of Gynecology & Obstetrics*, *131*(3), 219–225.Dickie, M., & Gerking, S. (1992). Willingness to pay for ozone control: Inferences from the demand for medical care. *Journal of Environmental Economics and Management*, *21*(1), 1–15.

Doremus, J. M., Jacqz, I., & Johnston, S. (2022). Sweating the energy bill: Extreme weather, poor households, and the energy spending gap. *Journal of Environmental Economics and Management*, *112*, 102611.

Drupp, M. A., Kornek, U., Meya, J. N., & Sager, L. (2021). *Inequality and the environment: The economics of a two-headed hydra* (CESifo Working Paper No. 9447). CESifo.

Du, D., & Karolyi, S. A. (2023). Energy transitions and household finance: Evidence from US coal mining. *The Review of Corporate Finance Studies*, *12*(4), 723-760.

Dwyer, L. L., Minca, E. C., Yabes, J. G., Schenker, Y., Lewing, B. & Ersek, M. (2023). Disparities in lung cancer: A targeted literature review examining lung cancer screening, diagnosis, treatment, and survival outcomes in the United States. *Journal of Racial and Ethnic Health Disparities*, *11*(4), 1489–1506.

Edelberg, W., & Steinmetz-Silber, N. (2024). *The changing demographics of business ownership*. Brookings Institution. https://www.brookings.edu/articles/the-changing-demographics-of-business-ownership

Executive Order No. 12,866, 58 Fed. Reg. 51,735 (Sept. 30, 1993).

Executive Order No. 13,045, 3 C.F.R. 198 (1997).

Executive Order No. 14,215, 90 Fed. Reg. 10,447 (Feb. 24, 2025).

Fandiño-Del-Rio, M., Matsui, E.C., Calafat, A.M., Koehl, R., Botelho, J.C., Woo, H., Boyle, M., Hansel, N.N., McCormack, M., & Quirós-Alcalá, L. (2024). Recent use of consumer and personal care products and exposures to select endocrine disrupting chemicals among urban children with asthma. *Journal of Exposure Science and Environmental Epidemiology*, *34*(4), 646–656.

Farber, D. A. (2023). Inequality and regulation designing rules to address race, poverty, and environmental justice. *American Journal of Law and Equality, 3*, 2–52.

Farber, D.A. (2024). Inequality and regulation revisited. *American Journal of Law and Equality, 4*.

Fedinick, K. P., Taylor, S., & Roberts, M. (2019). *Watered down justice*. Natural Resources Defense Council.

Fernández Intriago, L. A. (2020). Carbon taxation, green jobs, and sectoral human capital [Unpublished manuscript].

Finkel, A.M. (2014). EPA underestimates, oversimplifies, miscommunicates, and mismanages cancer risks by ignoring human susceptibility. *Risk Analysis*, *34*(10), 1784-1785.

Fiscella, K., & Sanders, M. R. (2016). Racial and ethnic disparities in the quality of health care. *Annual Review of Public Health*, *37*(1), 375-394.

Fullerton, D. (2011). Six distributional effects of environmental policy. *Risk Analysis: An International Journal*, *31*(6), 923-929.

Fullerton, D., & Heutel, G. (2010). Analytical general equilibrium effects of energy policy on output and factor prices. *B.E. Journal of Economic Analysis & Policy*, *10*, 79.

Gamper-Rabindran, S., & Timmins, C. (2011). Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. *American Economic Review*, *101*(3), 620–624.

Gamper-Rabindran, S., & Timmins, C. (2013). Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. *Journal of Environmental Economics and Management*, *65*(3), 345–360.

Ganapati, S., Shapiro, J. S., & Walker, R. (2020). Energy cost pass-through in US manufacturing: Estimates and implications for carbon taxes. *American Economic Journal: Applied Economics*, *12*(2), 303–342.

Gillingham, K., & Huang, P. (2025). Racial disparities in the health effects from air pollution: Evidence from ports. Journal of Human Resources, 60.

Ginsberg, G., Hattis, D., Russ, A., & Sonawane, B. (2005). Pharmacokinetic and pharmacodynamic factors that can affect sensitivity to neurotoxic sequelae in elderly individuals. *Environmental Health Perspectives*, *113(9)*, 1243.

Graff Zivin, J., & Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management, 58*(2), 119–128.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Graff Zivin, J., Neidell, M., & Schlenker, W. (2011). Water quality violations and avoidance behavior: Evidence from bottled water consumption. *American Economic Review*, *101*(3), 448–453.

Grainger, C. A. (2012). The distributional effects of pollution regulations: Do renters fully pay for cleaner air?. *Journal of Public Economics*, *96*(9-10), 840-852.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of Political Economy*, *110*(6), 1175-1219.

Greenstone, M., & Gallagher, J. (2008). Does hazardous waste matter? Evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, *123*(3), 951-1003.

Greenstone, M., He, G., Li, S., & Zou, E. Y. (2021). China's war on pollution: Evidence from the first 5 years. *Review of Environmental Economics and Policy*, *15*(2), 281–299.

Greenstone, M., & Jack, B. K. (2015). Envirodevonomics: A research agenda for an emerging field. *Journal of Economic Literature*, *53*(1), 5-42.

Hafstead, M. A. C., & Williams, R. C., III. (2020). Jobs and environmental regulation. *Environment and Energy Policy and Economics*, *1(1)*, 192.

Haninger, K., Ma, L., & Timmins, C. (2017). The value of brownfield remediation. *Journal of the Association of Environmental and Resource Economists*, *4*(1), 197-241.

Hanson, G. H. (2023). *Local labor market impacts of the energy transition: Prospects and policies* (NBER Working Paper No. 30871). National Bureau of Economic Research.

Haque, A. T., Berrington de Gonzalez, A., Chen, Y., Haozous, E. A., Inoue-Choi, M., Lawrence, W. R., McGee-Avila, J. K., Napoles, A. M., Perez-Stable, E. J., Taparra, K., Vo, J. B., Freedman, N. D., & Shiels, M. S. (2023). Cancer mortality rates by racial and ethnic groups in the United States, 2018-2020. *JNCI: Journal of the National Cancer Institute*, *115*(7), 822-830.

Harju, J., Kosonen, T., Laukkanen, M., & Palanne, K. (2022). The heterogeneous incidence of fuel carbon taxes: Evidence from station-level data. *Journal of Environmental Economics and Management*, 112.

Hassett, K. A., Mathur, A., & Metcalf, G. E. (2009). The incidence of a US carbon tax: A lifetime and regional analysis. *The Energy Journal*, *30*(2), 155-178.

Hill, R., Nguyen, T., & Daan, M. K. (2024). *Climate and equity: A framework to understand welfare impacts and guide policy action*. World Bank.

Hoffman, J. S., Shandas, V., & Pendleton, N. (2020). The effects of historical housing policies on resident exposure to intra-urban heat: A study of 108 US urban areas. *Climate*, *8*(1), 12.

Hornbeck, R., & Keskin, P. (2014). The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, *6*(1), 190-219.

Hsiang, S. M., & Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, *3*(02), 1250011

Hsu, A., Sheriff, G., Chakraborty, T., & Manya, D. (2021). Disproportionate exposure to urban heat island intensity across major U.S. *cities. Nature Communications*, *12*, 2721.

Hyland, C., & Laribi, O. (2017). Review of take-home pesticide exposure pathway to children living in agricultural areas. *Environmental Research*, *156*, 559–570.

Institute for Policy Integrity. (2017, February). *Does environmental regulation kill or create jobs?* https://policyintegrity.org/files/media/Jobs_and_Regulation_Factsheet.pdf

Ito, K., & Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in China. *Journal of Political Economy*, *128*(5), 1627–1672.

Jalan, J., Somanathan, E., & Chaudhuri, S. (2009). Awareness and the demand for environmental quality: Survey evidence on drinking water in urban India. *Environment and Development Economics*, *14*(6), 665–692.

Jayachandran, S. (2022). How economic development influences the environment. *Annual Review of Economics*, *14*, 229–252.

Jbaily, A., Zhou, X., Liu, J., Lee, T.-H., Hsu, Y.-M., Dominici, F., & Ebisu, K. (2021). Air pollution exposure disparities across US population and income groups. *Nature*, *601*(7892), 228–233.

Johansson, H., Mersha, T. B., Brandt, E. B., & Hershey, G. K. K. (2019). Interactions between environmental pollutants and genetic susceptibility in asthma risk. *Current Opinion in Immunology*, *60*, 156–162.

Joselow, M. (2025, September 16). E.P.A. to stop collecting emissions data from polluters. *New York Times*. https://www.nytimes.com/2025/09/12/climate/epa-emissions-data-collection-halt.html

Joselow, M. (2026, January 21). Trump's E.P.A. has put a value on human life: Zero dollars. *New York Times*. https://www.nytimes.com/2026/01/21/climate/epa-human-life-value.html

Josey, K. P., Delaney, S. W., Wu, X., Nethery, R. C., DeSouza, P., Braun, D., & Dominici, F. (2023). Air pollution and mortality at the intersection of race and social class. *New England Journal of Medicine*, *388*(15), 1396–1404.

Kalweit, A., Herrick, R. F., Flynn, M. A., Spengler, J. D., Berko Jr, J. K., Levy, J. I., & Ceballos, D. M. (2020). Eliminating take-home exposures: recognizing the role of occupational health and safety in broader community health. *Annals of work exposures and health*, *64*(3), 236-249.

Khanna, G., Liang, W., Mobarak, A. M., & Song, R. (2025). The productivity consequences of pollution-induced migration in China. *American Economic Journal: Applied Economics*, *17*, 194.

Kioumourtzoglou, M.-A., Schwartz, J. D., Weisskopf, M. G., Melly, S. J., Wang, Y., Dominici, F., & Zanobetti, A. (2016). PM2.5 and mortality in 207 U.S. cities: Modification by temperature and city characteristics. *Epidemiology*, *27*(2), 221–227.

Koman, P. D., Hogan, K. A., Sampson, N., Mandell, R., Coombe, C. M., Tetteh, M. M., Hill-Ashford, Y. R., Wilkins, D., Zlatnik, M. G., Loch-Caruso, R., Schulz, A. J., & Woodruff, T. J. (2018). Examining joint effects of air pollution exposure and social determinants of health in defining "at-risk" populations under the Clean Air Act: susceptibility of pregnant women to hypertensive disorders of pregnancy. *World medical & health policy*, *10*(1), 7-54.

Konisky, D. M. (2009). Inequities in enforcement? Environmental justice and government performance. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, *28*(1), 102-121.

Konisky, D. M., & Schario, T. S. (2010). Examining environmental justice in facility-level regulatory enforcement. *Social Science Quarterly*, *91*(3), 835-855.

Kotchen, M. J. (2021). The producer benefits of implicit fossil fuel subsidies in the United States. *Proceedings of the National Academy of Sciences*, *118*(14), e2011969118.

Kremer, M., Leino, J., Miguel, E., & Zwane, A. P. (2011). Spring cleaning: Rural water impacts, valuation, and property rights institutions. *The Quarterly Journal of Economics*, *126*(1), 145-205.

Kuehn, R. R. (1996). The environmental justice implications of quantitative risk assessment. *University of Illinois Law Review*, *1996*(1), 103-172.

Lee, H., & Porell, F. W. (2020). The effect of the Affordable Care Act Medicaid expansion on disparities in access to care and health status. *Medical Care Research and Review*, *77*(5), 461-473.

Levinson, A. (2019). Energy efficiency standards are more regressive than energy taxes: Theory and evidence. *Journal of the Association of Environmental and Resource Economists*, *6*(S1), S7-S36.

Liss, D. T., & Baker, D. W. (2014). Understanding current racial/ethnic disparities in colorectal cancer screening in the United States: the contribution of socioeconomic status and access to care. *American Journal of Preventive Medicine*, *46*(3), 228-236.

Liu, Y., Chen, X., Huang, S., Tian, L., Lu, Y., Mei, Y., Song, Y., Li, M., Chen, Y., & Kan, H. (2019). Short-term exposure to ambient air pollution and asthma mortality. *American Journal of Respiratory and Critical Care Medicine*, *200*(1), 24–32.

Locke, D. H., Hall, B., Grove, J. M., Pickett, S. T. A., Ogden, L. A., Aoki, C., Boone, C. G., O'Neil-Dunne, J. P. M., Wilson, M. A., & Troy, A. (2021). Residential housing segregation and urban tree canopy in 37 US cities. *Urban Sustainability*, *1*(1), 15.

Mahajan, S., Caraballo, C., Lu, Y., Valero-Elizondo, J., Massey, D., Annapureddy, A. R., Roy, B., Riley, C., Murugiah, K., Onuma, O., Nunez-Smith, M., Forman, H. P., Nasir, K., Herrin, J., & Krumholz, H. M. (2021). Trends in differences in health status and health care access and affordability by race and ethnicity in the United States. *JAMA*, *326*(7), 637-648.

Martin, O., Scholze, M., Ermler, S., McPhie, J., Bopp, S. K., Kienzler, A., Parissis, N. (2021). Ten years of research on synergisms and antagonisms in chemical mixtures: A systematic review and quantitative reappraisal of mixture studies. *Environment International*, *146*, 1.

Martinez-Morata, I., Bostick, B. C., Conroy-Ben, O., Duncan, D. T., Jones, M. R., Spaur, M., Patterson, K. P., Prins, S. J., Navas-Acien, A., & Nigra, A. E. (2022). Nationwide geospatial analysis of county racial and ethnic composition and public drinking water arsenic and uranium. *Nature Communications*, *13*, 7465.

Mathur, A., & Morris, A. C. (2014). Distributional effects of a carbon tax in broader U.S. fiscal reform. *Energy Policy, 66,* 326–334.

Medina-Ramón, M., Zanobetti, A., & Schwartz, J. (2006). The effect of ozone and PM10 on hospital admissions for pneumonia and chronic obstructive pulmonary disease: A national multicity study. *American Journal of Epidemiology, 163*(6), 579–588.

Miller, N. H., Osborne, M., & Sheu, G. (2017). Pass-through in a concentrated industry: Empirical evidence and regulatory implications. *The RAND Journal of Economics, 48*(1), 69–93.

Morgenstern, R. D., Pizer, W. A., & Shih, J. S. (2002). Jobs versus the environment: an industry-level perspective. *Journal of Environmental Economics and Management*, *43*(3), 412-436.

Motsinger-Reif, A. A., Reif, D. M., Akhtari, F. S., House, J. S., Campbell, C. R., Messier, K. P., Fargo, D. C., Bowen, T. A., Nadadur, S. S., Schmitt, C. P., Pettibone, K. G., Balshaw, D. M., Lawler, C. P., Newton, S. A., Collman, G. W., Miller, A. K., Merrick, B. A., Cui, Y., Anchang, B., Harmon, Q. E., McAllister, K. A., & Woychik, R. (2024). Gene-environment interactions within a precision environmental health framework. *Cell Genomics*, *4*(7), 100591.

Muehlegger, E., & Sweeney, R. L. (2022). Pass-through of own and rival cost shocks: Evidence from the U.S. fracking boom. *The Review of Economics and Statistics*, *104*(6), 1361–1369.

Moya, J., Bearer, C. F., & Etzel, R. A. (2004). Children's behavior and physiology and how it affects exposure to environmental contaminants. *Pediatrics*, *113*(4), 996–1006.

National Research Council. (1994). *Science and judgment in risk assessment*. National Academies Press.

National Research Council. (2004). *Stress. In R. A. Bulatao & N. B. Anderson (Eds.), Understanding racial and ethnic differences in health in late life: A research agenda*. National Academies Press.

National Research Council. (2009). *Science and decisions: Advancing risk assessment*. National Academies Press.

Neidell, M. (2010). Air quality warnings and outdoor activities: Evidence from Southern California using a regression discontinuity design. *Journal of Epidemiology and Community Health, 64*(10), 921-926.

Nielsen, G. H., Heiger-Bernays, W. J., Levy, J. I., White, R. F., Axelrad, D. A., Lam, J., Chartres, N., Panagopoulos Abrahamsson, D., Rayasam, S. D. G., Shaffer, R. M., Zeise, L., Woodruff, T. J., & Ginsberg, G. L. (2023). Application of probabilistic methods to address variability and uncertainty in estimating risks for non-cancer health endpoints. *Environmental Health*, *22*(1), 12.

Office of Management and Budget. (2025, April 17). *Memorandum M-25-24: Interim guidance implementing section 3 of Executive Order 14215* (pp. 2–4).

O'Neill, M. S., Zanobetti, A., & Schwartz J. (2005). Disparities by race in heat-related mortality in four US cities: The role of air conditioning prevalence. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *82*(2), 191–197.

Padula, A., Rivera-Nuñez, Z., & Barrett, E.S. (2020). Combined impacts of prenatal environmental exposures and psychosocial stress on offspring health: air pollution and metals. *Current Environmental Health Reports, 7*(2), 89-100.

Pais, J., Crowder, K., & Downey, L. (2013). Unequal trajectories: racial and class differences in residential exposure to industrial hazard. *Social Forces*, *92*(3), 1189–1215.

Park, S. K., O'Neill, M. S., Wright, R. O., Hu, H., Vokonas, P. S., Sparrow, D., & Schwartz, J. (2006). HFE genotype, particulate air pollution, and heart rate variability: A gene–environment interaction. *Circulation, 114*(25), 2798–2805.

Patel, S. A., Ali, M. K., Narayan, K. M. V., & Mehta, N. K. (2015). County-level variation in cardiovascular disease mortality in the United States in 2009–2013: Comparative assessment of contributing factors. *American Journal of Epidemiology*, *182*(11), 933–943.

Payne-Sturges, D. C., Cory-Slechta, D. A., Puett, R. C., Thomas, S. B., Hammond, R., & Hovmand, P. S. (2021). Defining and intervening on cumulative environmental neurodevelopmental risks: introducing a complex systems approach. *Environmental Health Perspectives, 129*(3), 35001.

Payne-Sturges, D.C., Scammell, M.K., Levy, J.I., Cory-Slechta, D.A., Symanski, E., Carr Shmool, J.L., Laumbach, R., Linder, S., & Clougherty, J.E. (2018). Methods for evaluating the combined effects of chemical and nonchemical exposures for cumulative environmental health risk assessment. *International Journal of Environmental Research and Public Health, 15(*12), 2797.

Pizer, W., & Sexton, S. (2019). The Distributional impacts of energy taxes. *Review of Environmental Economics and Policy, 13*(1), 104–123.

Price, J. H., Khubchandani, J., McKinney, M., & Braun, R. (2013). Racial/ethnic disparities in chronic diseases of youths and access to health care in the United States. *BioMed Research International*, *2013*, 787616.

Probst, J. C., Bellinger, J. D., Walsemann, K. M., Hardin, J., & Glover, S. H. (2011). Higher risk of death in rural blacks and whites than urbanites is related to lower incomes, education, and health coverage. *Health Affair*, *30*(10), 1872–1879.

Raimi, D., Carley, S., & Konisky, D. M. (2022). Mapping county-level vulnerability to the energy transition in US fossil fuel communities. *Scientific Reports, 12*, 15748.

Rausch, S., Metcalf, G. E., & Reilly, J. M. (2011). Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics, 33*.

Revesz, R. L. (2018). Regulation and distribution. *New York University Law Review*, *93*, 1499.

Revesz, R. L., & Ünel, B. (2023). Just regulation: Distributional analysis in agency rulemaking. *Ecology Law Quarterly*, *50*, 727.

Revesz, R. L., & Yi, S. P. (2022). Distributional consequences and regulatory analysis. *Environmental Law*, *52*, 53.

Rios, R., Poje, G. V., & Detels, R. (1993). Susceptibility to environmental pollutants among minorities. *Toxicology and Industrial Health*, *9*(5), 797–820.

Risher, J.F., Todd, D.G., Meyer, D., & Zunker, C.L. (2010). The elderly as a sensitive population in environmental exposures: Making the case. *Reviews of Environmental Contamination and Toxicology, 207,* 95-157.

Robinson, L. A., Hammitt, J. K., & Zeckhauser, J. R. (2016). Attention to distribution in US regulatory analyses. *Review of Environmental Economics and Policy*, *10*(2), 308-328.

Rustagi, A. S., Byers, A. L., & Keyhani, S. (2022). Likelihood of Lung Cancer Screening by Poor Health Status and Race and Ethnicity in US Adults, 2017 to 2020. *JAMA Network Open, 5*(3).

Sager, L., & Singer, G. (2025). Clean identification? the effects of the Clean Air Act on air pollution, exposure disparities, and house prices. *American Economic Journal: Economic Policy, 17*(1), 1–36.

Salvo, A. (2020). Local pollution as a determinant of residential electricity demand. *Journal of the Association of Environmental and Resource Economists*, *7*(5), 837–872.

Sarpong, S.B., Hamilton, R.G., Eggleston, P.A., & Adkinson, N.F. (1996). Socioeconomic status and race as risk factors for cockroach allergen exposure and sensitization in children with asthma. *Journal of Allergy and Clinical Immunology, 97*(6), 1393-1401.

Schlenker, W., & Roberts, M.J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America, 106*(37), 15594-15598.

Scott, M., Grineski, S. E., Collins, T. W., & Adkins, D. E. (2025). Climate gaps: Disparities in residential air conditioning access across ten US metropolitan areas. *Applied Geography*, *176*.

Sexton, K., & Hattis, D. (2007). Assessing cumulative health risks from exposure to environmental mixtures—three fundamental questions. *Environmental Health Perspectives*, *115*(5), 825.

Shrestha, R., & Saha, D. (2023). *US energy communities often face multiple health and workforce development challenges*. World Resources Institute. https://www.wri.org/insights/disadvantaged-energy-communities-analysis

Sieg, H., Smith, V. K., Banzhaf, H. S., & Walsh, R. (2004). Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review*, *45*(4), 1047–1077.

Silva, E., Rajapakse, N., & Kortenkamp, A. (2002). Something from "Nothing" − eight weak estrogenic chemicals combined at concentrations below NOECs produce significant mixture effects. *Environmental Science & Technology, 36*(8), 1751-1756.

Sinden, A. (2019). The problem of unquantified benefits. *Environmental Law, 49*(1).

Sly, P.D., & Flack, F. (2008). Susceptibility of children to environmental pollutants. *Annals of the New York Academy of Sciences, 1140,* 163-183.

Sosa, E., D'Souza, G., Akhtar, A., Sur, M., Love, K., Duffels, J., Raz, D. J., Kim, J. Y., Sun, V., & Erhunmwunsee, L. (2021). Racial and socioeconomic disparities in lung cancer screening in the United States: A systematic review. *CA: A Cancer Journal for Clinicians*, *71*(4), 299–314.

Spina, F. (2015). Environmental justice and patterns of state inspections. *Social Science Quarterly*, *96*(2), 417–429.

Stensrud, M. J., & Valberg, M. (2017). Inequality in genetic cancer risk suggests bad genes rather than bad luck. *Nature Communications*, *8*(1), 1165.

Stolper, S. (2024). *Income and energy tax pass-through: Evidence from gas stations* (Working paper).

Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. *Ecological Economics*, *131*, 468–474.

Thrupp, T.J., Runnalls, T.J., Scholze, M., Kugathas, S., Kortenkamp, A., & Sumpter, J.P. (2018). The consequences of exposure to mixtures of chemicals: Something from 'nothing' and 'a lot from a little' when fish are exposed to steroid hormones. *The Science of the Total Environment, 619-620*, 1482-1492.

Timmins, C., & Vissing, A. (2022). Environmental justice and Coasian bargaining: The role of race, ethnicity, and income in lease negotiations for shale gas. *Journal of Environmental Economics and Management*, *114*, 102657.

Tra, C. I. (2010). A discrete choice equilibrium approach to valuing large environmental changes. *Journal of Public Economics, 94*(1–2), 183–196.

U.S. Department of Health and Human Services, Office of Minority Health. (2025, January). *Asthma and Black/African Americans.* http://minorityhealth.hhs.gov/node/39/revisions/2564/view

U.S. Department of the Treasury. (2025). *Racial differences in economic security: Housing.* https://home.treasury.gov/news/featured-stories/racial-differences-in-economic-security-housing

U.S. Environmental Protection Agency (2008). *Child-specific exposure factors handbook*. https://assessments.epa.gov/risk/document/&deid%3D199243.

U.S. Environmental Protection Agency (2010). *Handbook on the benefits, costs, and impacts of land cleanup and reuse*. https://www.epa.gov/sites/default/files/2017-08/documents/ee-0569-02.pdf

U.S. Environmental Protection Agency (2011). *Exposure factors handbook* (pp. 1-10–1-12). https://www.epa.gov/expobox/exposure-factors-handbook-2011-edition.

U.S. Environmental Protection Agency (2018). *Strengthening transparency in regulatory science*, 83 Fed. Reg. 18768 (proposed Apr. 30, 2018).

U.S. Environmental Protection Agency (2021a). *Strengthening transparency in pivotal science underlying significant regulatory actions and influential scientific information*, 86 Fed. Reg. 469 (Jan. 6, 2021).

U.S. Environmental Protection Agency (2021b). *Strengthening transparency in pivotal science underlying significant regulatory actions and influential scientific information; implementation of vacatur*, 86 Fed. Reg. 29515 (June 2, 2021).

U.S. Environmental Protection Agency (2023). *Technical guidance for assessing environmental justice in regulatory analysis* (EPA-100-R-23-002).

U.S. Environmental Protection Agency (2024). *Final regulatory impact analysis for the reconsideration of the national ambient air quality standards for particulate matter*. https://www.epa.gov/system/files/documents/2024-02/naaqs_pm_reconsideration_ria_final.pdf

U.S. Environmental Protection Agency (2025a). *Critical Air Pollutants: NAAQS Table.* https://www.epa.gov/criteria-air-pollutants/naaqs-table

U.S. Environmental Protection Agency (2025b). *CGE modeling for regulatory analysis*. https://www.epa.gov/environmental-economics/cge-modeling-regulatory-analysis

U.S. Environmental Protection Agency (2026). *History of children's environmental health protection at EPA*. (2025, March 13). U https://www.epa.gov/children/history-childrens-environmental-health-protection-epa

Varshavsky, J. R., Rayasam, S. D., Sass, J. B., Axelrad, D. A., Cranor, C. F., Hattis, D., Hauser, R., Koman, P. D., Marquez, E. C., Morello-Frosch, R., Oksas, C., Patton, S., Robinson, J. F., Sathyanarayana, S., Shepard, P. M., & Woodruff, T. J. (2023). Current practice and recommendations for advancing how human variability and susceptibility are considered in chemical risk assessment*. Environmental Health, 21*(S1).

Vivier, P. M., Hauptman, M., Weitzen, S., Bell, S., Quilliam, D., & Logan, J. R. (2011). The important health impact of where a child lives: Neighborhood characteristics and the burden of lead poisoning. *Maternal and Child Health Journal*, *15*(8), 1197–1205.

Voorheis, J. (2017). *Longitudinal environmental inequality and environmental gentrification: Who gains from cleaner air?* U.S. Census Bureau, Center for Administrative Records Research and Applications.

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *Quarterly Journal of Economics*, *128*(4), 1787-1835.

Wang, X., Deltas, G., Khanna, M., & Bi, X. (2021). Community pressure and the spatial redistribution of pollution: The relocation of toxic-releasing facilities. *Journal of the Association of Environmental and Resource Economists, 8*(3).

Wang, Y., Shi, L., Lee, M., Liu, P., Di, Q., Zanobetti, A., & Schwartz, J.D. (2017). Long-term exposure to PM2.5 and mortality among older adults in the southeastern US. *Epidemiology, 28*(2), 207-214.

Ward-Caviness, C. K. (2019). A review of gene-by-air pollution interactions for cardiovascular disease, risk factors, and biomarkers. *Human Genetics, 138*(6), 547–561.

West, S. E., & Williams, R. C. (2004). Estimates from a consumer demand system: Implications for the incidence of environmental taxes. *Journal of Environmental Economics and Management*, *47*(3), 535–558.

White House Council of Economic Advisers. (2022). Accelerating and smoothing the clean energy transition. In Economic Report of the President.

Wolverton, A. (2009). Effects of socio-economic and input-related factors on polluting plants' location decisions. *The B.E. Journal of Economic Analysis & Policy, 9*(1), 27.

Wolverton, A. (2023). Environmental justice analysis for EPA rulemakings: Opportunities and challenges. *Review of Environmental Economics and Policy*, *17*(2), 346–353.

Wu-Williams, A.H., Zeise, L., & Thomas, D. (1992). Risk assessment for aflatoxin b1: a modeling approach. *Risk Analysis: An Official Publication of the Society for Risk Analysis, 12*(4), 559-567.

Yip, C. M. (2018). On the labor market consequences of environmental taxes. *Journal of Environmental Economics and Management*, *89*, 136-152.

Zhang, F. (2015). Energy price reform and household welfare: The case of Turkey. *The Energy Journal*, *36(2)*, 71-96.