The Distribution of Environmental Damages

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Introduction

Economists have long understood that the costs and benefits of environmental regulations are unlikely to be evenly distributed across individuals within a given population. There is a large and growing literature that explores how different environmental policy instruments produce winners and losers by imposing different regulatory costs on individuals (Baumol and Oates 1988; Parry et al. 2006; Fullerton 2017). However, environmental policy benefits are often more difficult to trace than costs because they consist of various nonmarket outcomes, such as health impacts, which are mediated by environmental conditions.

An environmental policy may generate an uneven distribution of benefits across populations if the policy delivers uneven quantities of an environmental good and/or the benefits from an incremental improvement in the environmental good differ across populations. The first case concerns how a policy affects the distribution of the environmental good itself (e.g., how a policy affects local air quality). While this concept is straightforward, there are significant challenges associated with both measuring changes in the quantity of the good across different populations and attributing observed changes to a particular policy. At the heart of the second case are questions about the underlying sources of heterogeneity in the benefits and/or damages associated with an incremental change in the environment. Such differences may stem from uneven baseline levels of exposure combined with nonlinear damage functions. Differences may also arise because damage functions differ across populations (e.g., due to differences in the underlying stock of health and/or defensive investments).[1] Individuals may also have different preferences for environmental goods that alter how

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[1]As we will discuss in the next section, we use "damage function" to refer to a function that translates exposure into differences in individual well-being or welfare (i.e., social costs).

exposure ultimately affects individual well-being or welfare. In cases where it is believed that environmental benefits are distributed unevenly, it is important to identify which of these underlying sources of heterogeneity in benefits is driving the unequal impact so that the distributional effects can be properly valued and addressed through policy.

To date, empirically identifying the causes of heterogeneous marginal damages has had only modest success. The main econometric challenge is that observable predictors of heterogeneity in damage functions (e.g., income) are not randomly assigned. This means that empirically determining what drives any uneven distribution of damages, whether it is income or one of many other factors correlated with income (e.g., air conditioning, baseline health status, or baseline exposure) is difficult. Nevertheless, it is important to solve this empirical problem, because identifying the determinants of heterogeneity in environmental benefits and damages is crucial for understanding their impact on welfare (Grossman 1972; Courant and Porter 1981; Bartik 1988).

This article discusses the current state of knowledge concerning the distribution of environmental policy benefits by reviewing the existing findings and identifying gaps in the empirical literature.[2] We begin in the next section by presenting a simple general framework that describes how environmental policy may generate distributional effects while also demonstrating where existing research findings "plug in." Then we apply this organizational framework to examine empirical research findings in three key areas: air pollution, deforestation, and climate change. For each topic, we examine whether there is evidence that populations face unequal exposure to different baseline levels of the environmental good, whether different populations appear to experience different marginal benefits from this good, and whether there is evidence concerning the drivers of these differences. Although these three topics have been studied at different spatial scales and with differing levels of sophistication, all three can be examined through our general framework. We believe this approach is useful because it highlights findings that may point towards the existence or absence of distributional effects; it is also helpful in determining what remains unknown. We present conclusions and future research priorities in the final section.

A General Framework for Examining the Distributional Impacts of Environmental Policy

This section provides a general framework for examining the sources of heterogeneity in environmental policy benefits. We start by framing the environmental impacts in terms of a function that links environmental exposure and attributes to the social cost or *damage*. We then discuss how the components of this function can manifest differently across different segments of the population, thus translating into heterogeneous policy impacts.

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[2]This article is part of a symposium on the distributional effects of environmental policy. The other articles in the symposium are Fullerton and Muehlegger (2019), which examines the distributional effects of environmental taxes and nontax regulations and discusses the distributional burdens of carbon policy, and Pizer and Sexton (2019), which focuses specifically on the distributional impacts of energy taxes.

Defining the Damage Function and its Components

An environmental externality (for simplicity, described here as a "damage"—i.e., a negative benefit) is a social cost that may be written as a general function of two components: the level of exposure to environmental conditions and a vector of socioeconomic attributes that may influence how exposure affects measures of economic well-being.[3] This *damage function* translates exposure and individual attributes into damages in welfare terms, such as willingness to pay (WTP). We define *exposure* as the state of the environment at an arbitrary point in time and space. For example, exposure refers to the physical amount of air pollutant, deforestation, and/or temperature that a location experiences at a moment in time. In most cases, exposure is measured in physical units that describe some dimension of the environmental system in question, such as "parts per million" for air pollution, "share of land cleared of trees" for ecosystem services, or "maximum daily temperature" for climate.[4] We note that the socioeconomic attributes that may interact with exposure through the damage function are potential underlying sources of *vulnerability*.

Sources of Vulnerability

Vulnerability, as it is usually defined in the literature,[5] is the rate at which exposure to an environmental condition generates harm given some initial social and environmental conditions; it is essentially the slope of the damage function given some initial socioeconomic attributes and environmental exposure. Vulnerability could depend on a wide range of factors that differ across individuals, such as baseline health, avoidance behavior (e.g., staying indoors when there is high air pollution), or defensive investments (e.g., buying an air conditioner). Many of these factors could be considered forms of human-made capital and thus their influence on the damage function can be viewed as indicating some substitutability or complementarity with forms of natural capital (Solow 2012), which here we would describe through the measure of environmental exposure. Thus, in this framework, exposure can be converted into terms of economic cost through a function that describes the vulnerability of an individual or population, that is, how exposure (treatments) translates into costs (treatment effects). In order to simplify the problem, we assume that, conditional on the same levels of exposure and socioeconomic attributes, the damage function is constant across individuals.

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[3]This function could be formally written as *Damage* = $f(e.x)$, where e is level of exposure and x is a vector of socioeconomic attributes.

[4]Some existing frameworks discussing air pollution damages distinguish between "ambient concentration" (the measured parts per million in the atmosphere), "dose" (how much did an individual ingest), "response" (the relationship between the dose and health outcomes), and "valuation" (the welfare costs of the health response). In our framework, e corresponds to ambient concentration (which is affected by policy) and $f(.)$ translates e into welfare terms. Differences in "dose," "response," and "valuation"—as they are used in that literature—are manifested through the different ways that the vector of attributes **x** mediate the translation of e into damage through $f(.)$.

[5]For example, the Intergovernmental Panel on Climate Change defines vulnerability as "the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt. A broad set of factors such as wealth, social status, and gender determine vulnerability and exposure to climate-related risk" (Oppenheimer et al., 2014).

Impact of a Policy Change

A policy change may alter the environmental exposure of an individual from its prepolicy value to a postpolicy value, producing a benefit equal to the corresponding change in damages.[6] Such a policy may have distributional consequences for two possible reasons. First, if the change in environmental exposure differs substantially across individuals, then the change in damages will also likely differ, regardless of the initial allocation of exposure or the structure of the damage function. Second, even if the change in exposure is relatively uniform across individuals, distributional effects may result from the policy if marginal damages (i.e., vulnerability) differ across individuals. Understanding the first case is primarily a challenge of simulating, forecasting, or measuring the response of physical systems (e.g., climate, pollution, forest density) to policies (Mauzerall et al. 2005; Hansen et al. 2013; Stocker 2014)—a challenging scientific task that is usually not under the purview of economists but is nonetheless essential to policy analysis (see, e.g., Muller and Mendelsohn [2009] and Fowlie, Holland, and Mansur [2012]). Understanding the second case remains a core challenge for empirical economists.

In general, if marginal damages are heterogeneous, then the benefits of an environmental policy will not be uniform across individuals. This is because some individuals will benefit (or be harmed) more or less from incremental changes in environmental conditions. In particular, if marginal damages are positively correlated with income levels, then policies that reduce exposure uniformly across a population will have regressive benefits because wealthier populations benefit more from the policy. If the correlation between marginal damages and income is negative, then such a policy would likely have progressive benefits.

As illustrated in the left panel of figure 1, heterogeneity in marginal damages may stem from nonlinearities in the relationship between exposure and damages, holding other factors constant (i.e., if damages are nonlinear with respect to exposure, then two individuals facing different baseline exposure will experience different marginal damages, even if they are identical in terms of all other factors that determine vulnerability). Alternatively—or in addition—heterogeneity in marginal damages may stem from heterogeneity in an underlying socio-economic attribute (e.g., baseline health) that controls how exposure translates into damages, shown in the right panel of figure 1.

Understanding the Sources of Heterogeneity

Identifying cases where marginal damages are heterogeneous is usually sufficient to conclude that environmental policy may have uneven benefits. However, designing efficient environmental policy and/or addressing any resulting distributional effects may require understanding the *source* of this heterogeneity. That is, do marginal damages differ because baseline exposure differs or because vulnerability differs? For example, does warming a country's climate harm poor countries more because they have greater vulnerability to climate (Dell, Jones, and Olken 2012) or because poor countries tend to be hotter and damages are nonlinear in temperature (Burke, Hsiang, and Miguel 2015)? These two different explanations for

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[6]For individual i with prepolicy exposure e_i and postpolicy exposure $e_i + \Delta e_i$, a policy generates benefits equal to the change in damages $f(e_i + \Delta e_i, x_i) - f(e_i, x_i)$.
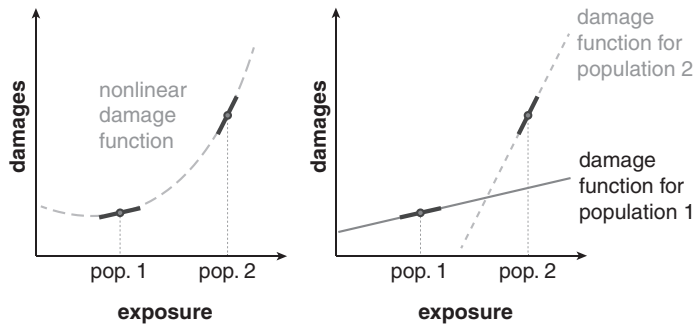
Figure 1 Heterogeneity in marginal damages result from nonlinear damage functions or differing vulnerability.

Notes: Different marginal effects are empirically measured (thick black tangent lines) for two populations at different exposure levels because there is a single nonlinear damage function (left panel) or the two populations exhibit different damage functions, that is, differing vulnerability, based on socioeconomic attributes that are correlated with exposure levels (right panel).

Source: The authors.

the same empirical observation (i.e., climate effects are greater in poor countries) generate highly divergent forecasts for global economic development in a scenario where countries both warm and become wealthier simultaneously, leading to different policy prescriptions. If vulnerability to heat results from being poor, then policies might focus on reducing future vulnerability by reducing future poverty, whereas if nonlinearities generate high marginal effects of heat regardless of income, then policies might focus on reducing overall exposure to heat by mitigating climate change. This example highlights the importance—for both economists and policymakers—of understanding the underlying sources for these types of heterogeneity.

In the next three sections we apply this framework to findings in the literature concerning the distribution of damages for air pollution, deforestation, and climate change. For each, we examine what the literature tells us about whether populations are unequally exposed to different baseline levels of the externality (or environmental good) in the cross section, whether populations exhibit heterogeneous marginal damages, and whether the evidence suggests that these differences are driven by nonlinear damage functions or heterogeneous damage functions.

Air Pollution

We begin with the most localized externality, air pollution. We first discuss some of the key measurement challenges. Then we survey the evidence on both how policy may differentially affect air pollution exposure and how individuals may be differentially affected by an incremental change in exposure

Measuring Exposure to Ambient Air Pollution Across the Population

Pollution data availability often precludes granular and/or spatially continuous analyses. This is true even for the United States, where only 1289 of 3144 counties had monitors for criteria

air pollutants (i.e., air pollutants that have been determined to be harmful to human health) at any time between 1990 and 2013. As a result, studies that examine differences in air pollution exposure have generally focused on a select set of cities for which detailed data are available (e.g., Depro, Timmins, and O'Neil 2015) or communities that are close enough to a facility that emits toxic air pollutants so that certain levels of exposure can be reasonably assumed (e.g., Been and Gupta 1997; Banzhaf and Walsh 2008). Recent advances in measurement and modeling (e.g., satellite remote sensing) are beginning to address some of these long-standing data challenges.

Evidence Concerning Cross-Sectional Patterns in Air Pollution Exposure

In the United States, cross-sectional differences in air pollution exposure are ubiquitous. A range of empirical papers that date back to the 1970s document that low-income individuals disproportionately live in areas with higher environmental risk (Freeman 1974; Harrison and Rubinfeld 1978) and closer to toxic facilities (Brooks and Sethi 1997), Superfund hazardous waste sites (Hamilton 1993; Currie 2011), and/or power plants (Davis 2011). However, due to the data and measurement challenges described earlier, the evidence on differences in air pollution exposure has been relatively indirect and piecemeal.

We shed some additional light on differential pollution exposure by using newly available, high-resolution data on ambient nitrogen dioxide (NO_2) levels in the United States (Novotny et al. 2011). We link these gridded pollution data to the 2010 U.S. census at the block group level and explore relationships between income and pollution exposure.[7] Figure 2A plots average NO_2 levels in each of the 932 Metropolitan Statistical Areas (MSAs) against the average MSA household-level income.[8] MSAs with higher average household income are also MSAs with higher average ambient NO_2 levels. This occurs because spatial heterogeneity in air pollution in the United States is closely tied to population density—cities are more polluted than rural areas on average and also have higher average income per capita.

However, data at the MSA level obscure a tremendous amount of variation in exposure levels at the *household* level. Figure 2B plots the relationship between block group household average income percentiles (based on the national block group income distribution) and average NO_2 levels in the block group income percentile. We see that, on average, there is a U-shaped relationship between income and exposure, with low- and high-income-percentile block groups in the United States disproportionately exposed to high ambient pollution levels relative to middle-income-percentile block groups. This finding can be partially reconciled with figure 2A by noting that some of the wealthiest and poorest block groups are both located in large MSAs, MSAs that on average have higher pollution levels.

It is important to note that the relationship between income and exposure within MSAs differs significantly from the national pattern. In order to examine the average within-MSA relationship between income and exposure, we separately compute the percentile of average income for each block group within each MSA. We then compute the average exposure level for each percentile and plot this relationship in figure 2C. In contrast with the correlation

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[7]A census block group is a geographical unit used by the U.S. Census Bureau. It is the smallest geographical unit for which the bureau publishes sample data from households.

[8]An MSA can be thought of as a broader metro area that surrounds a major city (e.g., the San Francisco MSA consists of San Francisco, Oakland, and Berkeley).
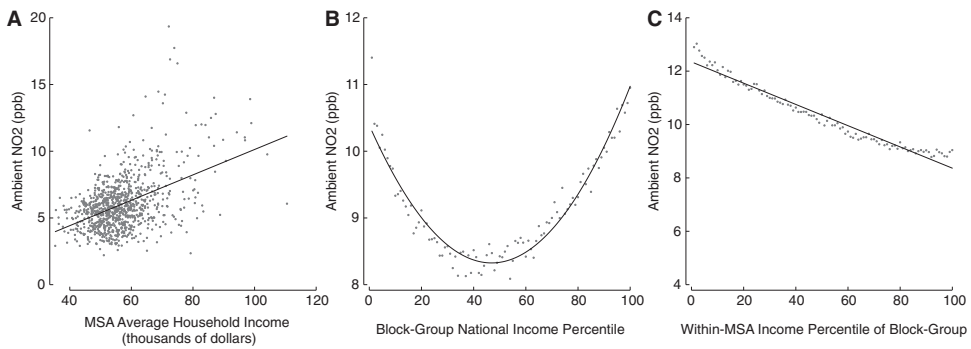
Figure 2   Relationships between NO_2 exposure and household income in the United States (2010). *Notes:* Panel A plots the relationship between the average Metropolitan Statistical Area (MSA) NO_2 levels and MSA-level household income. Panel B plots the relationship between the average NO_2 levels and the block group national income percentiles. Panel C plots the within-MSA relationship between NO_2 levels and MSA block group income percentiles.
Sources: Novotny et al. 2011 and 2010 U.S. census.

across MSAs, the average relationship between pollution exposure and income within MSAs is strictly negative. Similar disparities exist for other monitored criteria air pollutants.

It is also important to understand how these cross-sectional relationships change over time. One striking fact that emerges from extending our analysis above is that the gap in ambient air pollution levels between relatively affluent and less affluent households may be closing. Repeating the analysis in figure 2C using data from 2000 suggests that households in low-income areas of an MSA have seen much larger recent improvements in air quality relative to nearby households in wealthier block groups. While more research is needed to understand this pattern, such convergence in outcomes seems likely to be driven by the targeted nature of Clean Air Act (CAA) regulations. For example, the CAA abates pollution in areas of a city/county where pollution levels are highest, leading to relatively larger environmental benefits for poorer block groups within an MSA (Bento, Freedman, and Lang 2015).

Evidence of Heterogeneous Marginal Damages from Air Pollution

The persistent negative correlation between air pollution exposure and income per capita shown in figure 2 suggests that the burden of air pollution is not borne equally across the population. However, differences in exposure across income groups do not necessarily mean there are differences in damages or well-being. For example, if air quality is a normal good (i.e., demand increases with income), then lower-income households may choose to consume lower air quality in exchange for cheaper housing. In addition, individuals who choose to live in more polluted areas may have invested in measures to protect themselves against disproportionate exposure, such as by purchasing air filters. To identify whether differences in exposure correspond to differences in well-being, we need information on the marginal damage associated with a given level of exposure. Researchers have made substantial progress in understanding this issue over the past 15 years. Due to space constraints, we focus on a few studies that attempt to address what we believe are the key statistical challenges in this area, in particular those related to bias stemming from omitted variables.

Since the pioneering work by Chay and Greenstone (2003a, 2003b), researchers have been developing research designs that produce well-identified, causal estimates of the average effect of a one unit change in air pollution exposure on health and welfare. These approaches have allowed researchers to begin to explore heterogeneity in the causal effects of pollution exposure, which may be due to differences in observable characteristics of the population and/or nonlinearities in the damage function. For example, Chay and Greenstone (2003b) examine heterogeneity in the infant health dose–response function across different races and find that in their sample, African Americans respond more negatively than White Americans to increases in air pollution. Similarly, Currie and Walker (2011) find that traffic-related air pollution has larger health effects on African Americans than White Americans. Jayachandran (2009) notes a striking difference between richer and poorer places in terms of the mortality effects of pollution, and Arceo, Hanna, and Oliva (2016) find mortality effects of carbon monoxide (CO) in Mexico that are almost ten times higher than the effects found for U.S. populations (Currie and Neidell 2005). Schlenker and Walker (2015) find that people over the age of 65 years are more vulnerable to marginal changes in CO exposure. Similarly, Deschênes, Greenstone, and Shapiro (2017) find that exposure to nitrogen oxides has a significantly greater impact on mortality in the elderly.

These studies suggest that air pollution dose–response functions are heterogeneous across different subgroups of the population. However, there is much less evidence that these differences in health-related dose–response functions translate into differences in marginal damages or welfare. Moreover, attributing observable heterogeneity in a dose–response function and/or marginal damages to a single explanatory factor is challenging since the observed source of heterogeneity may be endogenous or correlated with important unobservable factors. For example, heterogeneity in pollution-induced mortality by income could arise because low-income individuals are more vulnerable to air pollution exposure—perhaps because of low baseline health or limited protective investments or because they disproportionately live in areas with higher levels of exposure and the dose–response function is nonlinear. If the dose–response function is nonlinear and the levels of baseline pollution exposure are different in rich and poor communities, then, as discussed earlier, the marginal effects will differ for the same dose–response function. Alternatively, or in addition, low-income individuals may have lower levels of baseline health, which means that a one unit increase in air pollution may lead to more severe mortality effects.

Few, if any, analyses explore the causes of treatment effect heterogeneity by examining exogenous variation in potential mediating factors (including baseline exposure), and this seems like a clear direction for future research. As discussed above, these distinctions matter for understanding the efficacy of any policy responses designed to alleviate any of the observed disparities. For example, did the CAA disproportionately improve the plight of some groups of individuals relative to others because it targeted locations with high baseline exposure levels? The impact of the law on air quality was spatially heterogeneous across the United States, begging the question as to how these changes were experienced by different subgroups of the population and how they affected the corresponding benefits. While the literature on the distributional benefits of the CAA tells us that air quality has improved disproportionately in low-income areas (e.g., Bento, Freedman, and Lang 2015), it says relatively little about whether these affected consumers differentially value the same marginal

improvement in air quality, making it difficult to determine whether CAA improvements in air quality are progressive or regressive. Thus, while it is clear that air pollution exposure differs dramatically across the population, and that environmental policy alters pollution exposure levels, it remains difficult to translate policy-induced changes in exposure into changes in economic welfare.

Forests and Associated Ecosystem Services

We next turn to ecosystem services, which encompass a large number of ways in which ecosystems benefit society. We limit our discussion to those services that accrue to nonowners of the resource, that is, those that are not completely internalized by the owners' use of the resource. Timber and nontimber products from a single-owner forest are not considered externalities, while pest control, soil fertility, and watershed services may constitute externalities when accrued to nonforest owners. This focus on externalities is important, as the existence of public benefits of ecosystems is what motivates many policy interventions, both from an efficiency standpoint and from any approach that values distributional effects. For our discussion, we focus on forests, as they are the source of numerous ecosystem services and their location, health, and evolution are relatively well documented. Greater availability of forest data has also facilitated research on this particular system, and thus a wider literature sheds light on patterns and sources of heterogeneity in ecosystem services from forests. Nevertheless, many of the conceptual and empirical issues that we highlight are common to ecosystem services that are not related to forests. We first discuss existing research and data on differences in exposure to deforestation. Then we discuss the ways in which the environmental benefits of forests may differ across individuals and how the literature has addressed these differences.

Evidence Concerning Cross-Sectional Patterns in Deforestation Exposure

Before turning to the existing literature, we present data from the World Bank Indicators to provide some descriptive statistics on the within- and between-country relationships between exposure to forest cover and various measures of socioeconomic status.[9] Figure 3A plots the cross-country relationship between forest cover (as a percentage of total land) and the logarithm of gross domestic product (GDP) per capita. This figure points to tremendous variation in forest endowments across both rich and poor countries. Thus if the marginal benefits of additional forest preservation were similar across countries, policies aimed at preserving current forest stocks across all countries would have neutral distributional effects.

Country averages are a relatively crude measure of exposure to forest ecosystem services and thus may mask important within-country heterogeneity. However, subnational data on

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[9]The cross-country relationship between income and deforestation has received substantial attention from studies testing for the existence of an "Environmental Kuznets Curve" (EKC), the idea that exposure to deforestation is higher for economies in transition undergoing rapid industrialization (Cropper and Griffiths 1994; Van and Azomahou 2007). Over time, as countries become wealthier, they tend to increase the area of land under protection (Frank and Schlenker 2016). Our goal here is not to revisit this literature but instead to document how forest exposure may differ across different subgroups and what that may mean for the regressivity/progressivity of various land use policies.
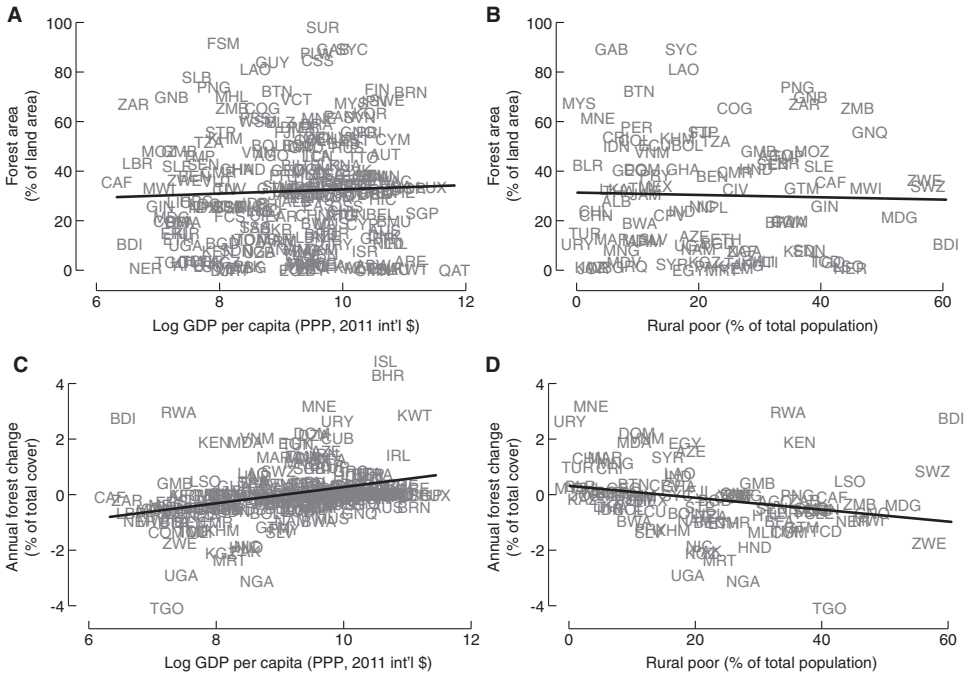
Figure 3 Cross-country associations between forest cover (2010), forest change (2000–2010), and economic measures.
Notes: Forest cover is shown as a percentage of total land area. GDP is in constant purchasing power parity terms.
Sources: WDI and authors' calculations.

exposure to forest cover linked to demographic characteristics is not available for many countries. The World Bank Indicators do provide information on the rural poor as a percentage of overall population. Thus, because forests are by definition rural, we use these data as a proxy for poverty to broadly examine whether relatively poor populations systematically have higher or lower exposure to forest ecosystem services. As shown in figure 3B, there appears to be no systematic relationship between the share of rural poor and forest cover. This suggests that even when we account for the relative size of the population that would most likely be exposed to ecosystem services (i.e., rural populations), exposure to forest cover is uniform across countries. This coarse proxy for poverty potentially near forests could mask important differences in actual forest endowments across income groups within a country, especially for the extreme poor. In fact, such within-country differences have been documented in the literature. For example, Mehta and Shah (2003) find that 84 percent of tribal ethnic minorities in India live in forested areas, and Li and Veeck (1999) and Sunderlin and Huynh (2005) find large overlaps between severe poverty and forests in China and Vietnam.

While forest stocks clearly play a role in the generation of ecosystem services, forest policies can potentially affect whether forest stocks are increasing or decreasing at a moment in time. Figures 3C and 3D plot the relationship between forest cover *changes* between 2000 and 2010 against GDP per capita and rural poverty, respectively. Positive numbers indicate afforestation and negative values denote deforestation. A clear positive relationship emerges between forest cover changes and income, with a corresponding negative relationship between forest

cover change and rural poverty. Afforestation rates are higher in wealthier countries, and differential forest protection may partially explain this pattern (Frank and Schlenker 2016). However, these countrywide measures of forest cover change may mask differences in exposure to deforestation *within* countries. For example, Andam et al. (2010) note that in Costa Rica and Thailand, communities near protected areas that reduced deforestation have below-average income. Thus, while there are clear differences in exposure to forest ecosystem services, much less is known about the extent to which incremental changes in exposure are valued differently by different subgroups of the population. As discussed earlier, differences in such marginal benefits are a key input for determining whether a policy is progressive or regressive with respect to benefits. We next examine the evidence on heterogeneous marginal benefits.

Evidence of Heterogeneous Marginal Damages from Deforestation

The evidence on heterogeneity in WTP for ecosystem services has generally used survey-based contingent valuation methods to explore how WTP varies with income. This literature consistently reports that the income elasticity for ecosystem services provided by forests and wetlands is less than one (Kristrom and Riera 1996; Hökby and Söderqvist 2003). An elasticity less than unity implies that a homogeneous increase in the exposure to the environmental amenity in question would disproportionately benefit low-income groups. However, contingent valuation methods and results have been heavily criticized (see, e.g., Diamond and Hausman [1994] and McFadden [1994]), and accordingly some researchers have tried to estimate income elasticities of demand for environmental goods directly. For example, Kahn and Matsusaka (1997) use voting data on environment-related propositions in California to estimate the demand elasticity with respect to income, obtaining a positive income elasticity for an array of measures, such as park bonds and the preservation of mountain lions and forests. It is only at high income levels that the number of votes begins to fall with income for some measures, such as park bonds. These results are consistent with the provision of parks being progressive for some ranges of income.

The empirical evidence pertaining to heterogeneity in the marginal benefits of forest management is relatively sparse. As mentioned earlier, understanding the underlying causes of heterogeneity is important for designing more effective policy solutions. More specifically, it is important to distinguish between nonlinearities, preference- and production-driven heterogeneity, and heterogeneity stemming from market failures that may disproportionately affect low-income groups. The presence of nonlinearities in the benefits of deforestation means policies that target areas with larger or smaller baseline forest stock could have a differential impact. As we have discussed, it appears that current afforestation and expansion of protected areas is disproportionately occurring in wealthier countries. However, the wide range of baseline forest cover, for all levels of income, combined with potential nonlinearities in benefits obscure the overall distributional consequences of these policies. There also may exist heterogeneity in estimated WTP stemming from uneven exposure to market failures (e.g., credit constraints and information imperfections). This heterogeneity is important because revealed preference methods that rely on assumptions pertaining to complete and well-functioning markets may not accurately reflect the true change in welfare in the presence of market failures. For example, a WTP income elasticity estimate that exceeds one could

stem from binding credit constraints for low-income individuals (Greenstone and Jack 2015). Differences in access to information across socioeconomic groups could also generate a misleading correlation (of either sign) between WTP and income.

It is difficult to distinguish empirically between sources of heterogeneity in the marginal benefits associated with the expansion of ecosystem services. However, a few studies provide evidence on the relative importance of different factors. For example, landscape diversity may lead to heterogeneity in the benefits associated with forest expansion. There may also be substitutes for ecosystem services (e.g., credit and insurance markets) that can insulate communities from damages associated with the depletion of the underlying resource. For example, populations that have sound health infrastructure may be less affected by deforestation-driven infectious diseases, such as malaria (Garg 2014). Relatedly, households that live near forest sometimes report using environmental extraction (e.g., consumption of bushmeat) as a mechanism for coping with economic shocks, such as crop failure or major livestock loss (Noack et al. 2016). Jayachandran et al. (2017) also find that farmers preserve more trees in response to payments for ecosystem services if they report having cut trees for large emergency expenses in the past, again pointing to missing insurance markets as a source of variation in marginal benefits. However, the diversity in the types of services that forests and other ecosystems provide suggests that many other sources of variation in benefits are plausible. In our view, this is clearly an area of research that requires additional empirical work.

Climate and Climate Change

The third environmental good we consider is the climate, which is affected by actions and policies that induce or mitigate climate change. Early economic assessments of climate change, such as the Dynamic Integrated Climate–Economy model developed by Nordhaus and Boyer (2000), were representative-agent models focused on intertemporal optimization (i.e., the distribution of benefits across generations). However, these models are unable to capture distributional effects among contemporaries because they contain only a single economic agent that experiences economic loss from climate change and thus there can be no inequality of damages. As research on the economics of climate (today) and climate change (in the future) has progressed, distributional effects among contemporaries have received increasing attention. We first discuss differences in exposure to current climates and future climate change across the globe and then discuss heterogeneity in the marginal damages associated with current climates and climate change.

Evidence Concerning Cross-Sectional Patterns in Climate Exposure

Current climatic conditions are primarily a function of geographic endowments, determined mainly by large-scale geophysical processes beyond the control of society. It is thought that these endowments may have persistent economic consequences, such as reducing economic productivity (Gallup, Sachs, and Mellinger 1999; Nordhaus 2006; Schlenker, Hanemann, and Fisher 2006; Hornbeck 2012b; Hsiang and Jina 2015). However, because populations might select into different climates based on their preferences (Acemoglu, Johnson, and Robinson 2001; Olmstead and Rhode 2011; Hornbeck 2012a; Albouy et al. 2016; Deryugina, Kawano, and Levitt 2018), it is challenging to measure the causal effects of natural endowments

directly. Nonetheless, the possibility of persistent economic effects of endowments has contributed to the "folk wisdom" in policy circles that poor populations are systematically exposed to the most damaging climates today and will face the largest changes in the future (Kahn 2005; Adger 2006; Intergovernmental Panel on Climate Change 2014; Hallegatte et al. 2016; World Bank 2017).

While it is true that poor populations tend to live in hotter and drier locations, both within and across countries (Nordhaus 2006; Park et al. 2015), there are notable exceptions both within countries (e.g., Florida, California, and Arizona in the United States) and across countries (e.g., Singapore and major oil-producing countries in the Middle East). Moreover, some evidence suggests this cross-sectional association has changed over time (Acemoglu, Johnson, and Robinson 2002). Still, tropical countries, which continue to be some of the poorest, are the most heavily exposed to damaging climatic phenomena, such as El Nino–Southern Oscillation (Hsiang and Meng 2015), although wealthy countries, such as Australia, are also exposed to some of these phenomena (Nicholls 1989).

In another example that counters the policy folk wisdom, we find that exposure to tropical cyclones[10] has a global baseline distribution across space that is spread fairly evenly across global income categories when computed at the "pixel" level in global data sets. Specifically, we find that approximately 35 percent of both the poorest third and the middle third of the global income distribution, and 45 percent of the richest third, are never exposed to a tropical cyclone (figure 4A). However, this slight high-income advantage is reversed when we consider the intensity of cyclones, since a modestly larger fraction of the richest third (70 percent versus 63 percent) is exposed to tropical cyclone winds of any intensity that is above "tropical storm" status. Perhaps the strongest counterexample to the policy folk wisdom is the global distribution of tornado events. Tornadoes require strong temperature and pressure gradients that exist only over land in the middle latitudes, so the populations exposed to tornadoes are almost exclusively high income (United States, Europe, and Australia) or middle income (South Africa, Argentina, and China) (Goliger and Milford 1998).

The projected distribution of exposure to *future* climate change is also more complex than the simple notion that poor countries will face the greatest exposure to damages, although there are aspects of these changes that are likely fairly regressive. Notably, there is a negative correlation between current average income and the magnitude of future average temperature changes across locations; thus average temperature changes are expected to be the largest in northern locations, which tend to be wealthier today, and smallest in the tropics (Stocker 2014; Hsiang and Sobel 2016). However, importantly, we find that changes in exposure to extremely hot temperatures (e.g., greater than 30°C), which are some of the most economically harmful conditions (Carleton and Hsiang 2016), will be much larger for the poorest and middle thirds of the global income distribution when these changes are evaluated at the pixel level (figure 4B).

Projected changes in rainfall are less certain and also show no clear association with current income, because in future projections, both rich and poor locations (e.g., southern Europe and the Caribbean) get drier and both rich and poor locations (e.g., the United States and the Sahel) get wetter on average (Stocker 2014). Changes in future tropical cyclone distributions are similarly unrelated to current incomes, with the strongest intensification expected in East

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[10]This class of phenomena includes hurricanes, typhoons and tropical storms.

A Global exposure to tropical cylones
in current climate, by income

B Global exposure to changes in temperature
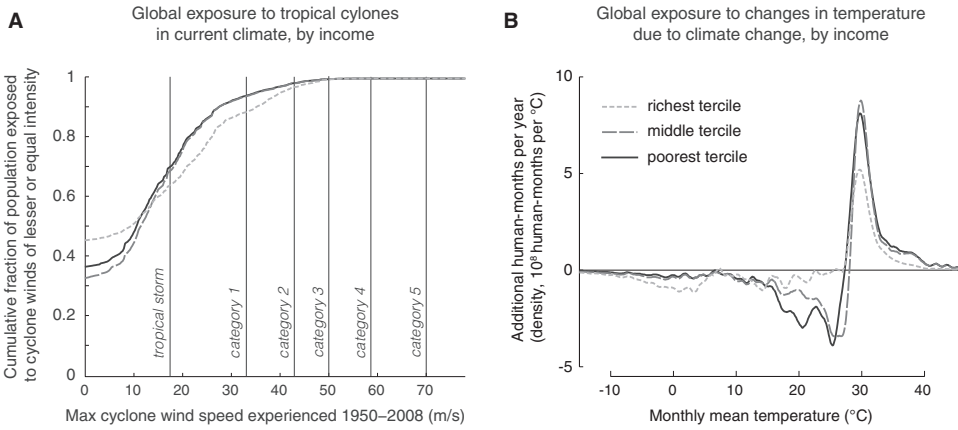due to climate change, by income

Figure 4   Distribution of exposure to modern tropical cyclones and future temperature changes by income.

Notes: Panel A plots the cumulative fraction of world population exposed to tropical cyclone winds (1950–2014) by tercile of the global income distribution (2000 estimate): dotted, richest; dashed, middle; solid, poorest. Vertical lines indicate wind speed thresholds (on the Saffir–Simpson scale). Panel B plots changes in the quantity of time the global population is exposed to different temperatures due to "business as usual" warming by 2100. Income terciles are the same as in panel A.

Sources: Coupled Model Intercomparison Project archive, International Best Track Archive for Climate Stewardship database, and authors' calculations.

Asia, a weakening in the Indian Ocean, and unclear changes in the Atlantic (Knutson et al. 2010).

   Thus, overall, exposure to future climate changes (in physical units) is not inherently greater for poorer populations. However, as we will discuss next, because of the heterogeneous marginal effects of these changes, it does appear likely that poor populations will face larger future damages from climate change.

Evidence of Heterogeneous Marginal Damages from Climate and Climate Change

The marginal damages of exposure to a climatic change may differ across populations, causing some populations to suffer larger damages even if all populations are exposed to changes of equal magnitude (e.g., $+1°C$ of warming). Here we will discuss evidence of such differences and their possible sources.

   Marginal damages from climatic conditions are usually compared among contemporaries across different locations, such as counties (e.g., Annan and Schlenker 2015) or countries (e.g., Hsiang, Meng, and Cane 2011), or within a fixed location but varying over time (e.g., Roberts and Schlenker 2011). When comparing marginal damages between contemporaries, a key question is whether a particular social or economic attribute of a population, such as higher income (e.g., Dell, Jones, and Olken 2012), causes the population to suffer larger or smaller damage from climatic exposure, or are populations that are more regularly exposed to a specific climate better able to cope with the type of events characteristic of that climate (e.g., Hsiang and Narita 2012). One hypothesis underlying the second case is that if populations experience a climatic event more frequently, then they may have learned about the event and invested in precautions that limit their losses each time the event occurs.

Simple comparisons of marginal effects across populations are primarily descriptive and generally cannot identify the cause for a population's vulnerability. Identifying such a cause requires exogenous variation in those factors that might be determinants of vulnerability. For example, Hsiang, Burke, and Miguel (2013) argue that if a hypothesized determinant of vulnerability were exogenously altered (e.g., incomes increased due to an abrupt transfer) and marginal damages from climate changed in response, that would provide evidence that the change in the altered factor (income) had a causal effect on vulnerability. Recent applications of this approach include a study showing that the rollout of an income insurance program in India reduced the likelihood that rainfall shortages trigger local violence (Fetzer 2014) and reduced the likelihood that temperatures affect children's test scores (Garg, Jagani, and Taraz 2017), indicating that income is indeed one determinant of these marginal effects. In other applications that use this approach to study whether access to technologies affects marginal damages, Hornbeck and Keskin (2014) show that access to irrigation technologies reduced the effects of drought on U.S. farmers, and Barreca et al. (2016) provide evidence that access to air-conditioning technologies reduced the marginal impact of temperature on mortality in the United States. These studies constitute a promising step forward in identifying factors that cause marginal damages of climate to differ between populations.

In many cases where marginal damages are found to differ significantly across populations, there may be economic explanations for these patterns. For example, Hsiang and Narita (2012) found that a high spatial concentration of capital in rich countries may lead to higher defensive investment and lower marginal damages from cyclones, and Davis and Gertler (2015) showed that patterns of temperature-related energy demand reflected the influence of income on air conditioning demand. In some cases, observed patterns of marginal damages appear consistent with certain patterns of market failure. For example, binding credit constraints in low-income contexts might explain why individuals underinvest in protective measures, such as air conditioning (Burgess et al. 2014), or adopt *ex post* coping strategies that may be effective in the short run but are costly in the long run, such as reducing investments in child health (Maccini and Yang 2009; Anttila-Hughes and Hsiang 2011) or engaging in transactional sex (Burke, Gong, and Jones 2015).

Notably, however, low- and high-income populations have been found to have similar marginal damages due to climate in several cases (Carleton and Hsiang 2016) even though one might expect wealthy populations to exhibit lower vulnerability, as was the case in the examples above. For example, Hsiang and Jina (2014) examine the long-run effect of tropical cyclones on GDP growth and show that the relative income losses per unit of exposure for rich and poor countries appear to be almost identical. Determining why rich and poor populations exhibit similar marginal damages in some cases and not others is an important challenge for future research.

Another major source of heterogeneity in marginal damages from climate stems from nonlinearities in the damage function, which may exist even if all economic factors are held "fixed." A nonlinear damage function indicates that the marginal damages from a change in climate depend on a population's initial climate, and thus their initial position on the damage function, since different portions of the function may exhibit a steeper or shallower slope (recall figure 1). Nonlinear responses to climate have been identified in a number of contexts, including studies of the effect of temperature on crop yields (Schlenker and Roberts 2009; Schlenker and Lobell 2010), mortality (Deschênes and Greenstone 2011),

energy demand (Aroonruengsawat and Auffhammer 2011), social instability (Hidalgo et al. 2010), property crime (Ranson 2014), permanent migration (Bohra-Mishra, Oppenheimer, and Hsiang 2014), labor supply (Graff Zivin and Neidell 2014), human emotion (Baylis 2015), cognitive performance (Graff Zivin, Hsiang, and Neidell 2018), human capital formation (Park 2017), and income (Burke, Hsiang, and Miguel 2015; Deryugina and Hsiang 2017; Isen, Rossin-Slater, and Walker 2017). Across these contexts, marginal damages tend to increase, sometimes dramatically, at higher temperatures (with the exception of property crime).

An important implication of nonlinear damage functions is that they can still generate distributional impacts that increase or decrease inequality even when they are identical across rich and poor subpopulations. One way this can occur is if the baseline climate of rich and poor populations differs systematically, such that the two groups are located at different positions on the damage function and thus have different marginal damages from climate. For example, Hsiang et al. (2017) demonstrate that strong nonlinearities in damage functions lead to higher damages from global warming in the hot southern United States relative to the cooler north. Because southern counties also tend to be poorer on average, the distribution of damages from warming increase preexisting patterns of inequality, with poorer and hotter southern counties harmed more than richer and cooler northern counties.

To summarize, both rich and poor populations are exposed to some types of adverse climates and both are expected to experience climate changes of comparable physical magnitudes. However, poorer populations tend to exhibit larger marginal damages from climatic changes and thus similar physical changes generally impose greater damage on these poorer populations. The larger marginal damages for poor populations may have economic origins, such as less access to credit or technology, or they may be due to nonlinear damage functions, since poor populations tend to inhabit locations today whose baseline climates correspond with the steeper portions of damage functions. In most cases, designing effective policy to reduce the distributional effects of warming will require determining the specific cause of these unequal marginal damages.

Conclusions and Priorities for Future Research

Researchers have long considered whether some populations, particularly the poor, bear a disproportionate share of the burden of environmental damages. In this article we have presented an approach to evaluating this question empirically, decomposing the problem into an evaluation of whether exposure to quantities of environmental goods differs between rich and poor populations and an evaluation of whether marginal damages from a unit of exposure differs between rich and poor populations. We have summarized what is known regarding both of these subproblems for air pollution, deforestation, and climate change, demonstrating the generalizability of this framework.

We find that recent work indicates that in some cases the poor do disproportionately bear the burden of environmental damages, while in others the data contradict this intuition. In many cases, poorer populations tend to be exposed to higher levels of air pollution and deforestation, but not necessarily larger climate changes. However, across all three domains, there is some evidence that marginal changes in environmental exposure tend to impose larger marginal damages on poor populations.

A pervasive challenge throughout the literature is the difficulty of identifying the causes of differing marginal damages between rich and poor populations. The possible presence of nonlinear damage functions and nonuniform exposure further complicates the task of determining whether marginal damages fundamentally differ across groups. In order to design effective policies that will address the distributional consequences of environmental exposure, it is crucial to understand the underlying causes of heterogeneity in marginal damages. Therefore, systematically isolating and empirically testing the role of hypothesized causes should be a priority for future research. In particular, as mentioned earlier, a promising first step is to identify settings in which researchers can combine exogenous variations in an environmental exposure variable and quasi-experimental variation in a hypothesized cause of heterogeneous marginal damages, such as income transfers or access to a new defensive technology.

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