NBER WORKING PAPER SERIES

THE DISTRIBUTION OF ENVIRONMENTAL DAMAGES

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Working Paper 23882
http://www.nber.org/papers/w23882

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2017

We would like to thank Hannah Druckenmiller, Eyal Frank, Don Fullerton, Teevrat Garg, Peiley Lau, and Joseph Shapiro for helpful comments. Andres Gonzalez, Sahaab Sheikh and Eva Lyubich generously provided research assistance for this project. All errors are our own The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 23882
September 2017
JEL No. H23,I14,Q5,Q56

ABSTRACT

Most regulations designed to reduce environmental externalities impose costs on individuals and firms. An active body of research has explored how these costs are disproportionately born by different sectors of the economy and/or across different groups of individuals. However, much less is known about the distributional characteristics of the environmental benefits created by these policies, or conversely, the differences in environmental damages associated with existing environmental externalities. We review this burgeoning literature and develop a simple and general framework for focusing future empirical investigations. We apply our framework to findings related to the economic impact of air pollution, deforestation, and climate, highlighting important areas for future research. A recurring challenge to understanding the distributional effects of environmental damages is distinguishing between cases where (i) populations are exposed to different levels or changes in an environmental good, and (ii) where an incremental change in the environment may have very different implications for some populations. In the latter case, it is often difficult to empirically identify the underlying sources of heterogeneity in marginal damages, as damages may stem from either non-linear and/or heterogeneous damage functions. Nonetheless, understanding the determinants of heterogeneity in environmental benefits and damages is crucial for welfare analysis and policy design.

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Economists have long understood that the benefits to environmental regulations are unlikely to be evenly distributed across individuals within a given population. As early as the 1980's, researchers and policy makers became specifically concerned that lower income populations might be disproportionately exposed to and impacted by environmental externalities, such as air and water pollution, leading rise to the notion of "environmental justice" (see e.g., US GAO (1983) and United Church of Christ (1987)). We review and discuss what is understood about the distribution of environmental benefits (or conversely, damages), while highlighting how policies designed to mitigate environmental damages alter this distribution. An established literature has long considered 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), but because a large share of environmental benefits correspond to non-market outcomes, such as health impacts, they are often more difficult to trace than the direct pecuniary costs of the regulation itself. Due to this difficulty, it is not generally known if most environmental policies are, on net, progressive, regressive, or have no distributional effects (Fullerton, 2011; Parry et al., 2006; Bento, 2013).

In our exploration of what is known empirically about the distribution of environmental benefits, we organize our discussion using a general framework that highlights the underlying sources of heterogeneity in these benefits, while also discussing what these underlying sources may suggest for welfare analysis and/or policy-making. Our framework is intentionally simple, focusing on the structure of damage functions and the key challenges that we see in the literature: separating out heterogeneity in damages that originate from differences in environmental exposure, differences in damage functions across individuals, and/or non-linearities within a single damage function. Then, to demonstrate its generality, we examine three core areas of study in empirical environmental economics—pollution, deforestation, and climate change—through this lens. These three topic areas are generally considered at three very different spatial scales and are currently studied with differing levels of sophistication. However, all three can be placed in our common framework, demonstrating its broad applicability.

An environmental policy may generate an uneven distribution of benefits across populations if (*i*) the policy delivers uneven quantities of an environmental good and/or (*ii*) the benefits from an incremental improvement in the environmental good differ across populations. The first case is largely a question of policy design and the physical relationships that govern the distribution of the environmental good—these factors sound straightforward, but challenges associated with measurement of unevenly distributed environmental goods are often substantial. At the heart of second case lie questions about the underlying sources of heterogeneity in benefits/damages associated with an incremental change in the environment. These differences may stem from uneven baseline levels of exposure combined with non-linear dose-response functions. These differences may also arise because dose-response functions differ across populations (e.g., due to differences in the underlying stock of health and/or differences in defensive investments). Individuals might also have differing preferences over environmental goods that potentially alter how dose-response relationships map into individual well-being or welfare. In cases where environmental benefits are thought to be distributed unevenly, identifying which of these mechanisms drives the unequal impact is key to understanding how distributional effects should be valued and possibly ameliorated through policy.

To date, empirically identifying the causes of heterogeneous marginal damages has had only modest success. Econometrically, the core difficulty is that observable predictors of heterogeneity in dose-response functions (e.g., income) are not randomly assigned. Thus, empirically determining what drives any observed heterogeneity in a dose-response, whether it is income or one of many other factors correlated with income (e.g., defensive investments, health stock, or baseline exposure), is difficult. Nonetheless, solving this empirical problem is important because the source of heterogeneity matters when translating estimates of dose-response functions into welfare metrics or marginal damages (Grossman, 1972; Courant and Porter, 1981; Bartik, 1988). This identification challenge plagues many environmental policy contexts and will likely require creative research designs to solve.

Structure of the problem

We believe it useful to break down the central conceptual components associated with environmental externalities and the ways that they are differentially manifested among segments of the population. Broadly speaking, heterogeneity in damages from externalities can stem from differences in exposure and/or differences in marginal damages, conditional on exposure.

An environmental externality (described here as a "damage," i.e. negative benefit, for simplicity) is a cost that may be written as a general function of two components: the level of exposure to environmental conditions e and a vector of attributes $\mathbf{x}$ that may influence how exposure affects measures of economic well-being:

$$Damage = f(e, \mathbf{x})$$

where $f(.)$ is a function that translates exposure and individual attributes into damages in welfare terms, such as a willingness-to-pay. We define exposure e 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.[1] We note that the vector of attributes $\mathbf{x}$ that translate exposure into damages are potential underlying sources of *vulnerability*, i.e. factors that may make individuals more vulnerable to exposure by making it costlier for them to experience. Vulnerability, could depend on a wide range of factors that differ across individuals–such as baseline health, avoidance behavior, or defensive investments. Many of these factors could be considered forms of human-made capital and thus their influence on $f(.)$ may be understood to indicate some substitutability or complementarity with the form of natural capital described by e (Solow, 2012). Thus, in this framework, exposure is only converted into terms of economic cost through a function that describes the vulnerability of an individual or population, i.e. how exposure (treatments) translate into costs (treatment effects). By way of an example using air pollution–exposure refers to the amount of the harmful air pollutant in the atmosphere, whereas vulnerability, which depends on $\mathbf{x}$, tells us how that concentration will ultimately translate into changes in individual welfare.

A policy change may alter the exposure of individual i from its pre-policy state e_i to a post-policy state $e_i + \Delta e_i$, producing a benefit equal to the change in damages

$$\Delta Damage_i = f(e_i + \Delta e_i, \mathbf{x}_i) - f(e_i, \mathbf{x}_i)$$

making it clear that the policy may have distributional consequences for two possible reasons. First, if the change in environmental exposure Δe_i differs substantially across individuals, then the change in damages will also likely differ, regardless of what the initial allocation of e_i is or the structure of $f(.)$. Second, even if the change in exposure is relatively uniform across individuals (perhaps because

[1] 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 $\mathbf{x}$ mediate the translation of e into damage through $f(.)$.

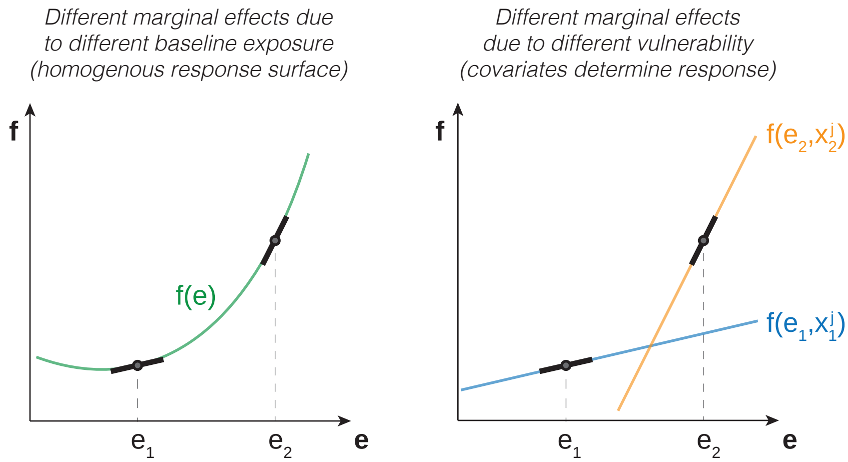

Figure 1: Different marginal effects are measured (black tangent lines) for two populations at different exposure levels (e_1 and e_2) because there is a single nonlinear damage function (left) or the two populations exhibit different damage functions, i.e. differing *vulnerability*, based on attributes (x_1^j and x_2^j) that are correlated with exposure levels.

it is marginal for all i), distributional effects may result from the policy if marginal damages

$$\frac{\partial Damage_i}{\partial e} = \frac{\partial f(e_i, \mathbf{x}_i)}{\partial e}$$

differ across individuals. Understanding the first case is primarily a challenge of simulating, forecasting or measuring the response of physical systems 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 which 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, heterogeneity in marginal damages generates distributional effects of environmental policy benefits, since some individuals will benefit or be harmed more or less for incremental changes in environmental conditions. If marginal damages are positively correlated with income levels, then policies that reduce exposure uniformly across a population will have regressive benefits since wealthier populations benefit more from the policy. If marginal damages are negatively correlated, such a policy would have progressive benefits.

As illustrated in the left panel of Figure 1, heterogeneity in marginal damages could stem from non-linearities in the relationship between exposure and damages holding other factors constant, i.e. if $f(.)$

is non-linear with respect to e then two individuals facing different baseline levels e_i will experience different marginal damages, even if they are identical in terms of all other factors that determine vulnerability:

$$\frac{\partial^2 Damage}{\partial e^2} = \frac{\partial^2 f(e, \mathbf{x})}{\partial e^2} \neq 0$$

Alternatively—or in addition—heterogeneity in marginal damages may stem from heterogeneity in an underlying attribute, here the jth element in $\mathbf{x}$, that controls how exposure translates into damages, i.e. x^j may affect vulnerability:

$$\frac{\partial Damage}{\partial e \partial x^j} = \frac{\partial^2 f(e, \mathbf{x})}{\partial e \partial x^j} \neq 0$$

illustrated in the right panel of Figure 1.

Identifying cases where marginal damages are heterogenous 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. Do they 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 the same empirical observation generate highly divergent forecasts for global economic development in a scenario where countries both warm and become wealthier simultaneously, highlighting the importance of understanding underlying sources for these types of heterogeneity.

In cases where heterogeneous marginal damages generate distributional impacts of environmental policies, empirically decomposing the sources of heterogeneity is important for understanding the social costs of environmental externalities and for considering potential policy interventions. Moreover, the extent to which we can extrapolate damages measured in one population to others depends on our understanding of how heterogeneity in damages is manifested.

Two practical empirical considerations

Beyond standard econometric concerns regarding causal inference and the identification of marginal effects (see e.g., Angrist and Pischke (2010)), two particularly important and general measurement issues arise when trying to understand the distributional benefits of environmental services and/or policy.

First, many policies or exogenous events will change environmental exposure in different areas by different quantities. Measuring these heterogenous changes in exposure is difficult because data measuring exposure is often imperfect and/or incomplete. Moreover, mismeasurement of exposure can exacerbate the challenges associated with understanding the nature and magnitude of heterogeneous marginal damages. Since marginal damages are measured in cost per unit of exposure, comparing marginal damages across contexts requires that marginal losses are identified relative to an objective and physically consistent measure of exposure. This can present a challenge when comparing marginal damages if the spatial scales of measurement for exposure vary substantially across studies (e.g., examining pixels vs. countries) or if exposure is encoded using context-specific and/or non-physical units. For example, it is often econometrically convenient to transform environmental exposure into a binary variable, such as encoding observations with high levels of deforestation or tropical cyclone strikes as a dummy variable equal to one. However, such an approach may not allow meaningful comparisons of marginal damages across contexts since variation in physical exposure experienced by populations may differ dramatically between observations that are all encoded using a common "treated" dummy.

The second measurement challenge stems from the difficulty at empirically distinguishing between the two cases in Figure 1, even when levels of environmental exposure are well measured and heterogenous marginal effects are convincingly estimated. This identification problem stems primarily from the fact that researchers often observe only a single tangency on a dose-response function, rather than the entire function for different sub-groups. Thus, when researchers observe differences in marginal effects, it may be hard to identify if these differences stem from different points on the same, non-linear dose response function or points on different dose-response functions. For example, baseline levels of environmental exposure (e_i) are rarely randomly assigned, and they are often correlated with covariates $\mathbf{x}_i$. For this reason it is often difficult to demonstrate that there exists a homogenous and nonlinear response function (left panel of Figure 1). Moreover, even if levels of environmental treatment e are randomly assigned, the covariates $\mathbf{x}$ are usually not, making it difficult to pin down which elements in $\mathbf{x}$ cause differences between dose-response functions. As highlighted above, understanding the reasons for which dose-response functions differ is crucial both for valuing damages as well as understanding how damages may be mitigated through policy. For example, if we observe different dose-response functions for different income groups, these differences in responses may not be driven by income but instead some other correlated unobservable (e.g., baseline health stock). The ideal solution to this identification problem would be a situation in which we observe exogenous variation in (i) baseline exposure, (ii) changes in exposure, and (iii) changes in observable predictors of heterogeneity (e.g., income, air conditioning, or other defensive investments). However, since these conditions are rarely met, this has become a difficult empirical problem—although we will point towards research designs that approximate this ideal setup below.

Some observations and questions regarding air pollution, deforestation, and climate

We now discuss several findings and provide new analysis regarding the distribution of benefits for three broad classes of widely studied environmental externalities—air pollution, deforestation, and climate change. These three examples span the possible spatial dimensions of impact, from local to regional to global. We apply the framework above by separately considering whether populations are unequally exposed to different baseline levels of the externality (or environmental good) in the cross-section, whether different populations exhibit heterogenous marginal damages, and, if so, whether there is evidence that these differences are driven by nonlinear damage functions or heterogenous damage functions (i.e. differing vulnerability).

We point to numerous remaining gaps in the literature while also providing some suggestions as to how researchers may make progress in these areas. We do not intend to be comprehensive, but instead we focus on results which highlight various aspects of the research frontier and which demonstrate the importance of carefully measuring exposure while considering nonlinearity and other forms of heterogeneity. We begin with the most localized externality, air pollution, then proceed to questions related to deforestation and ecosystems services, which have distributional consequences at somewhat larger spatial scales. We then conclude by discussing climate impacts and climate change, which can have distributional effects across very large spatial scales.

Air pollution

Pollution data availability often precludes granular and/or spatially continuous analyses. Even in the United States (US) it remains difficult to measure exposure to air pollution: of 3144 counties, only 1289 have monitors for criteria air pollutants at any point between 1990-2013. As a result, studies exploring differential air pollution exposure have generally focused on a select set of cities where detailed data are available (e.g., Depro, Timmins, and O'Neil (2015)) or communities that are sufficiently proximate to a facility that emits toxic air pollutants such that certain levels of exposure can reasonably be assumed (e.g., Been and Gupta (1997); Banzhaf and Walsh (2008)). Recent advances in measurement and modeling may address some of these longstanding data challenges. For example, researchers have recently created ambient pollution data products for the US over time by merging fixed-site pollution monitors, satellite- derived NO_2 estimates, and GIS-derived land-use data (see e.g., Novotny et al. (2011)). These granular and spatially continuous air pollution measures may afford researchers new possibilities, such as the ability to connect pollution exposure with high resolution demographic data. We use the data from Novotny et al. (2011) to explore differences in pollution exposure across US Census Block-Groups.[2]

Some cross-sectional patterns in air-pollution exposure

In the US, cross-sectional differences in air pollution exposure are ubiquituous. A range of empirical papers that date back to the 1970's documented that low income individuals disproportionately live in areas with higher environmental risk (Freeman, 1974; Harrison and Rubinfeld, 1978), closer to toxic facilities (Brooks and Sethi, 1997) and Superfund hazardous waste sites (Hamilton, 1993; Currie, 2011), and/or power plants (Davis, 2011). However, the evidence on differences in air pollution exposure has been relatively indirect and piecemeal due to the measurement challenges described above. We shed some additional light on differential pollution exposure by using newly available, high-resolution data on ambient NO_2 levels in the US (Novotny et al., 2011). We link these gridded pollution data to the 2010 Decennial Census at the Block-Group level and explore relationships between income and pollution exposure. Figure 2A plots average NO_2 levels in each of the 932 Metropolitan Statistical Areas (MSA) against the MSA household-level income.[3] 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. Since cities, on average, have higher per capita income than rural areas, the unadjusted, cross-sectional correlation between between air pollution exposure and average household income in an MSA is positive.

[2] See Clark, Millet, and Marshall (2014) for a complementary descriptive exercise of pollution exposure using these same data.

[3] These MSA-level statistics are created by taking the population-weighted average of Block-Group pollution measures within an MSA. Block-Group income is reported as population counts in various income categories. We impute the average income in a Block-Group by taking the mid-point of the income bin and creating a population weighted average across income bins. For the unbounded top income category (i.e. income above $200,000) we use the $200,000 as opposed

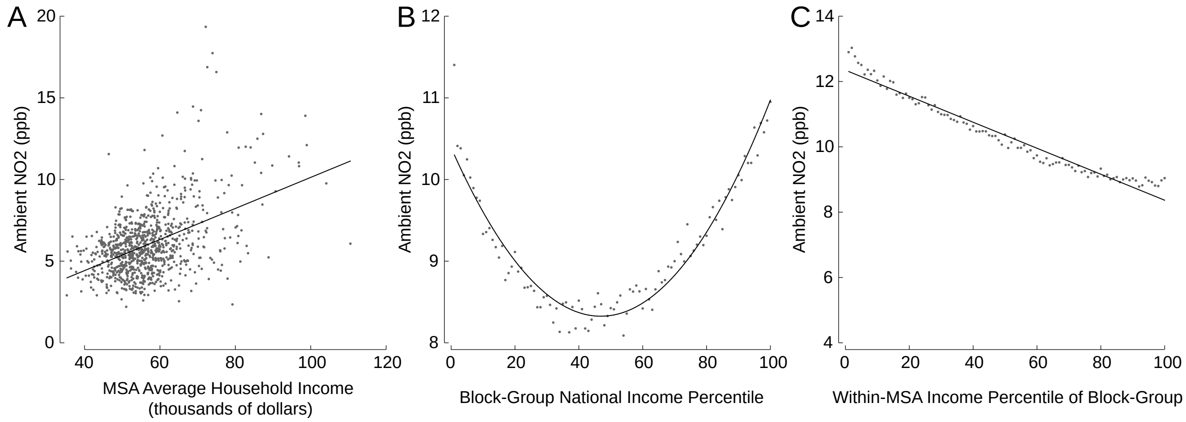

Figure 2: This figure presents three panels relating 2010 Census Block-Group NO_2 exposures to household income. Panel A plots the relationship between average MSA NO_2 levels and MSA-level household income. Panel B plots the relationship between average NO_2 levels and the Block-Group national income percentiles. Panel C plots the within-MSA relationship between NO_2 levels and MSA Block-Group income percentiles. See text for details. Source: Novotny et al. (2011) and 2010 Decennial Census.

However, MSA-level aggregates obscure a tremendous amount of household-level variation in exposure levels. 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 Block-Group income percentiles towards the center of the national income distribution. 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.

Importantly, national cross-sectional patterns differ from patterns of environmental exposures within a given MSA. In order to look at the average within-MSA relationship between income and exposure, we compute the percentile of average income for each Block-Group separately within each MSA. We then compute the average exposure level for each percentile and plot this relationship in Figure 2C. The within-MSA correlation appears to be opposite of what is observed across MSAs: the average relationship between pollution exposure and income *within* MSAs is strictly negative, with poorer areas in each MSA characterized by higher levels of ambient pollution than richer areas. Similar disparities exist for other monitored criteria air pollutants.

to an undefined mid-point.

An area of interest for future inquiry is 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).

Identifying heterogeneous marginal effects of air pollution

A persistent negative correlation between air pollution exposure and income per capita in the cross-section suggests that the air pollution burden is not borne equally across the population. However, disproportionate exposure need not necessarily mean disproportionate differences in damages or well-being. For example, if air quality is a normal good, then lower-income households may choose to consume less of the environmental good 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 the purchasing of air filters or buying bottled water. To understand whether differences in exposure correspond to differences in well-being, we need information on the marginal damage associated with a given level of exposure, an area where researchers have made substantial progress over the past 15 years. We discuss a few of these studies, focusing on work that attempts to address what we believe are the first order statistical challenges in this area – in particular concerns pertaining to bias stemming from omitted variables.

Starting with the pioneering work by Chay and Greenstone (2003a,b) researchers have exploited research designs appropriate for causal inference to deliver well-identified estimates of the average effect of a one unit change in air pollution exposure on health and welfare. These approaches allow researchers to begin exploring heterogeneity in the causal effects of pollution exposure, possibly caused by differences in observable characteristics of the population and/or non-linearities in the dose-response function. For example, Chay and Greenstone (2003b) explore heterogeneity in the infant-health dose-response function across different races – finding that African Americans have more negative health responses to increases in air pollution than do Whites in their sample. Similarly, Currie and Walker (2011) observe that health effects of traffic related air pollution are larger for African Americans relative to Whites. Jayachandran (2009) observes a striking difference in the mortality effects of pollution between richer and poorer places. Arceo, Hanna, and Oliva (2016) find that the mortality effects of carbon monoxide in Mexico are almost ten-times the effects found in similar estimates for US populations (Currie and Neidell, 2005). Schlenker and Walker (2015) find those over the age of 65 are more vulnerable to marginal changes in carbon monoxide exposure (CO) and, similarly, Deschenes, Greenstone, and Shapiro (Forthcoming) observe significantly larger responses in elderly mortality to variation in NOx exposure.

The evidence above suggests 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 underlying explanatory factor 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 non-linear. If the dose-response function is non-linear and rich and poor communities have unequal levels of baseline pollution exposure, then marginal effects will differ for the same dose-response function (i.e. left panel of Figure 1). Alternatively, or in addition, low income individuals may have lower levels of baseline health for which a one unit increase in air pollution can lead to more severe mortality effects (i.e. right panel of Figure 1). Few, if any, analyses explore the causes of treatment effect heterogeneity by exploiting 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.

Some policy discussions concerning air pollution

Even with well-identified *average* dose-response functions, understanding the distributional benefits of air pollution policy remains challenging. One difficulty stems from the fact that the underlying source of heterogeneity in dose-response function matters for welfare and incidence of a policy. For example, if some individuals invest in defensive behavior, which alters the dose-response relationship for this sub-population, then the costs of these investments should be included in estimates of the marginal damage (Grossman, 1972; Courant and Porter, 1981; Bartik, 1988). The absence of random variation in the observable predictors of treatment effect heterogeneity make it difficult to pinpoint the precise source of heterogeneity – a crucial ingredient for welfare analysis. Future researchers therefore must develop creative research designs to understand the distributional benefits of environmental policies. 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 law leads to substantial spatial heterogeneity in the way in which it impacts air quality around the United States, begging the question as to how these changes map to different subgroups of the population and the corresponding benefits. Moreover, it might be the case that improvements in environmental quality affect market prices and/or wages in ways that could differentially impact household welfare, and understanding the distributional impacts of environmental policy requires researchers to grapple with these general equilibrium issues. For example, Bento, Freedman, and Lang (2015) show that lower-income homeowners tended to enjoy the greatest benefits from the 1990 CAAA, as these were the homeowners located in areas that experienced the largest improvements in air quality. Based on house price appreciation, households in the lowest quintile of the income distribution received annual benefits from the program equal to 0.3% of their income on average during the 1990s, over twice as much as those in the highest quintile. However, higher-income households are more likely to be homeowners, and thus may be more likely to reap the benefits of any capitalization of environmental improvements into property values (Grainger, 2012). While the literature on the distributional benefits of the Clean Air Act tells us that air quality has improved disproportionately in low income areas, it says relatively little about how low income consumers differentially value the same marginal improvement in air quality. More generally, understanding how willingness to pay for non-market amenities varies with income is a fundamental question for discussing incidence of environmental benefits, but the existing evidence is weak and indirect – much of the observed heterogeneity observed in WTP by income may be driven by other observable or unobservable factors that are simply correlated with income.

Deforestation and associated ecosystem services

Ecosystem services encompass a broad number of ways in which ecosystems benefit society. We limit our discussion to those services that accrue to non-owners of the resource; i.e. those that are not completely internalized by the owners' use of the resource. Timber and non-timber products from a single-owner forest are not considered externalities; while pest control, soil fertility, and watershed services may constitute externalities when accrued to non-forest owners. This distinction 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.

Even within this narrower definition of ecosystem services, the measurement of their benefits faces a unique challenge – namely, the diverse nature and geographic scope of all externalities that fall in this category. Ecosystem services as externalities emerge from a wide array of human interactions with nature. For example, humans rely on forests for watershed services, erosion prevention, soil fertility, local climate, global climate, preservation of biodiversity, recreation, etc. Other natural resources, such as water bodies, coral reefs, and wetlands, provide an equally diverse set of services. For our discussion of the distribution of benefits stemming from ecosystems we will focus on forests, as they are the source of numerous ecosystem services and their location, health, and evolution is 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.

The two main challenges associated with studying ecosystem services are measurement and valuation. Many of the services that forests provide, such as soil fertility, local biodiversity, erosion protection are often difficult to track and measure in a comprehensive way. Moreover, even if researchers could measure these services well, it is often difficult to estimate or measure how forest cover affects these services. Forests may affect other ecosystems in a variety of ways and at very different geographic scales. For example, while exposure to soil fertility benefits might be limited to a few meters from a forest, local biodiversity services (e.g., pest control) could extend up to 0.5-10 km from the forest's edge (Bianchi, Goedhart, and Baveco, 2008; Karp et al., 2013), and watershed services may extend to entire river basins, which can span several countries (Myers, 1997). Even if researchers are able to estimate the complex relationships between forest cover and other ecosystem services, it is exceedingly difficult to understand how these services are valued. There is rarely an observed market price for these services, and some of the services provided may benefit individuals thousands of miles away through recreational uses and/or "existence value". Researchers have used a wide variety of empirical methods to try to monetize these benefits, ranging from stated-preference, survey based methods to other revealed-preference methods, such as hedonic valuation. We discuss this literature in more detail below.

Some cross-sectional patterns in deforestation exposure

Before turning to the existing literature, we use 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.[4] Figure 3A plots the cross-country relationship between forest cover (as a percentage of total land) and the logarithm of 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 which might mask important within country heterogeneity. However, sub-national data on 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, and since forests are by definition rural, we can use this data to crudely explore whether relatively poor populations systematically have higher or lower exposure to forest ecosystem services. Figure 3B shows no systematic relationship between the share of rural poor and forest cover. Thus, even when conditioning on the relative size of population that would be most likely exposed to ecosystem services (i.e., rural populations), exposure to forest cover stocks appears 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. Some of these within-country differences have been documented by the literature. For example, 84% of tribal ethnic minorities in India live in forested areas (Mehta and Shah, 2003), and large overlaps between severe poverty and forests exist within China and Vietnam (Li and Veeck, 1999; Sunderlin and Huynh, 2005).

While forest stocks play a role in the generation of ecosystem services, forest policies operate on the margin of these stocks by altering flows, partially determining if stocks are increasing or decreasing at a moment in time. Figures 3C and 3D plot the relationship between forest cover *changes* between

[4]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 document how forest exposure may differ across different sub-groups and what that may mean for the regressivity/progressivity of various land use policies.

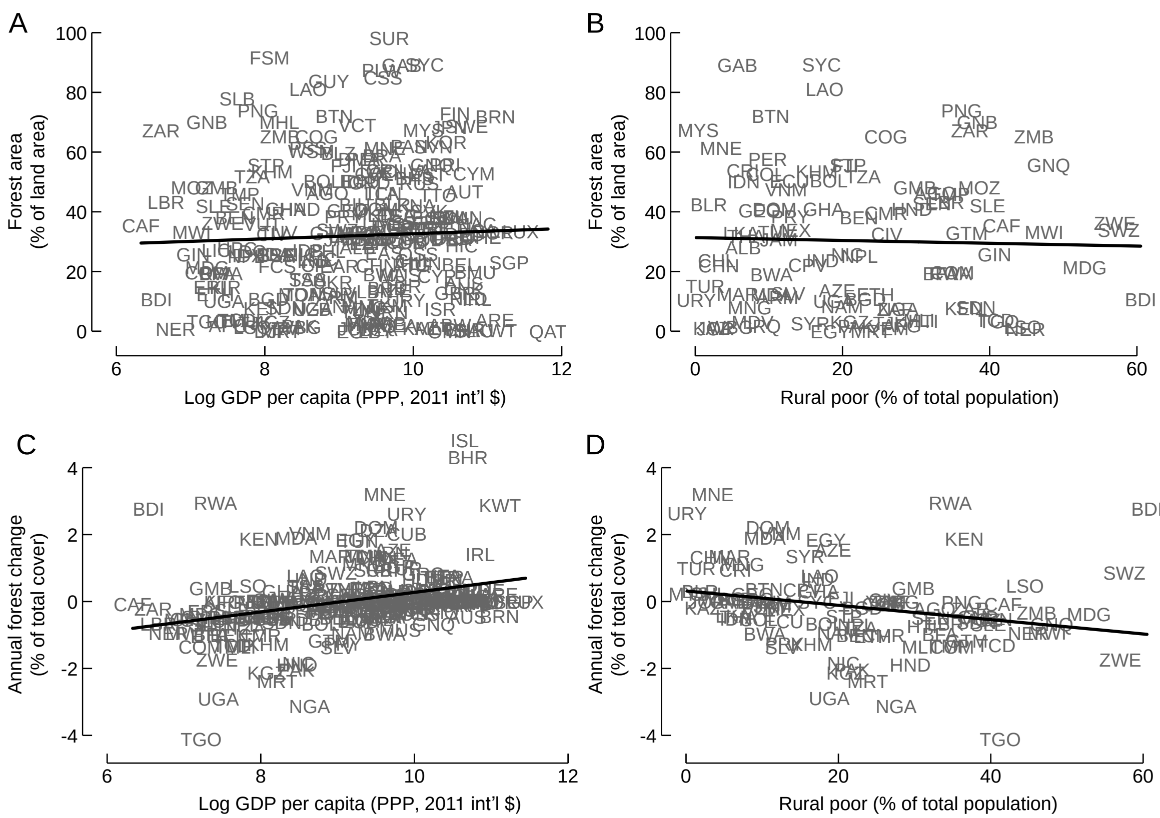

Figure 3: (A) Describes the cross-sectional relationship in 2010 between country-level percentage of forest cover and log GDP per capita in constant purchasing power parity terms. (B) Describes the cross-sectional relationship between country-level forest cover and rural poor as a share of the total population (i.e. the share of population most likely exposed to local and regional ecosystem services from forest). (C) Describes the cross-sectional relationship between the 2000-2010 change in forest cover (as percentage of total forest cover) and log GDP per capita in constant purchasing power parity terms. (D) Describes the cross-sectional relationship between the 2000-2010 change in forest cover (as percentage of total forest cover) and rural poor as a share of the total population. Source: World Development Indicators, World Bank (http://data.worldbank.org/data-catalog/world-development-indicators). Notes: Panels A and C include 232 countries with forest cover and income data in 2000 and 2010. Panels B and D include the subset of 98 countries with data on rural poor.

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). This being said, country-wide measures of forest cover change may mask differential exposure to deforestation within countries. For example, Andam et al. (2010) note that communities in Costa Rica and Thailand near protected areas that reduced deforestation have below-average income. While there is some evidence to suggest heterogeneity exists in exposure to ecosystem services, much less is known about how incremental changes in exposure may be differentially valued.

Identifying heterogeneous marginal effects of deforestation

The evidence on heterogeneity in WTP for ecosystem services has generally explored how WTP varies with income using survey-based, contingent valuation methods. 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 homogenous 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 begin 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.[5]

The empirical evidence of heterogeneity in marginal benefits is relatively sparse. As mentioned above, understanding the underlying causes of heterogeneity is important for designing more efficacious policy solutions. More specifically, it is important to distinguish between non-linearities, preference-

[5]Note that the income elasticity of demand can differ from the income elasticity of WTP when dealing with quantity-rationed collective goods (Hanemann, 1991; Flores and Carson, 1997). In such a case, the income elasticity of WTP is a sufficient statistic for benefit incidence, whereas the income elasticity of demand is typically not (Flores and Carson, 1997; Ebert, 2003).

and production-driven heterogeneity, and heterogeneity stemming from market failures that may disproportionately affect low income groups. The presence of non-linearities in benefits means policies that target areas with larger or smaller baseline forest stock could have a differential impact. As discussed earlier, 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 non-linearities 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 credit constraints binding for low income individuals (Greenstone and Jack, 2015). Differences in information across socioeconomic groups could also generate a misleading correlation (of either sign) between WTP and income.

Empirically, it is difficult to distinguish between sources of heterogeneity in marginal benefits associated with the expansion of ecosystem services, but a few studies provide evidence on the relative importance of different factors. For example, landscape diversity may be a potential source of environmental/ecosystem endowments that can lead to heterogeneity in benefits associated with forest expansion.[6] There may also be substitutes for ecosystem services that might insulate communities from any damages associated with the depletion of the underlying resource (e.g., credit and insurance markets). 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. (2016) also finds that farmers preserve more trees in response to payments to 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 the benefits are plausible. In our view, this is clearly an area of research that

[6] The marginal benefit of expansion may vary as a function of diversity – monocultures may enable agricultural insect pests to thrive due to an absence of predators and abundant food, necessitating greater insecticide use and possible negative impacts on human health, ecosystem services, and ecological communities (Larsen, 2013; Larsen, Gaines, and Deschênes, 2015).

will gain from additional empirical work.

A policy consideration regarding deforestation

A different but potentially important source of heterogeneity in benefits from ecosystem services discussed above are transfers that result from explicit ecosystem service transactions, such as payments for ecosystem services (PES). These transfers become available when the market failure externality associated with ecosystem destruction is internalized through market-driven compensation schemes – those who bear the opportunity cost of preserving the resource are compensated by those who experience the benefits it provides. Countries with poor governance, for example, may benefit less from these markets if they are unable to enforce contracts and agreements, making them less able to capitalize on the world-wide services their national ecosystems provide. Conte and Kotchen (2010) provides evidence consistent with low income countries having less credible enforcement of PES contracts, finding that the price of voluntary carbon offsets related to forestry is much lower for the poorest countries.

As Grieg-Gran, Porras, and Wunder (2005) note, the degree to which PES can benefit the poor likely depends (i) on how competitive low income populations are vis-a-vis other providers for similar services, (ii) on the rules of the program (or eligibility criteria), and (iii) on the transaction costs involved in securing the payments. They find that eligibility rules are the most salient feature of PES schemes that are likely to influence the distribution of a program's benefits in the five Latin American case studies. Some programs have hectare caps, to limit the amount of payments that go to large wealthy landowners. However, other rules, such as formal land ownership, may limit access to the program for the poor. Few empirical studies examine the distribution of PES payments across socioeconomic groups and their resulting welfare impact. The absence of empirical evidence is in part due to the paucity of socioeconomic information regarding participants and non-participants available to researchers. Alix-Garcia, Sims, and Yañez-Pagans (2015) examine the incidence of a large PES program in Mexico and is one of the few studies to collect such information. They find no distributional impacts stemming from differential exposure as "enrolled land had a similar degree of poverty as the national distribution". However, they find small progressive impacts stemming from differential marginal effects; consumption and investment appear to be slightly higher among the poorest recipients in the study. Additional research on the design and impact of PES programs, exploiting similarly granular data in other contexts, should be a high priority as decision-makers around the world increasingly employ these policies.

Climate and climate change

Early economic assessments of climate change, such as the DICE model developed by Nordhaus and Boyer (2000), were representative-agent models focused on inter-temporal optimization, i.e. the distribution of benefits across generations. However, these models are unable to capture distributional effects among contemporaries because only a single economic agent experiences economic loss from climate change. As research on the economics of climate (today) and climate change (in the future) has progressed, the importance of these contemporaneous distributional effects have gained increasing attention in both national (Deschenes and Moretti, 2009; Hsiang et al., 2017) and global contexts (Anthoff, Hepburn, and Tol, 2009; Burke, Hsiang, and Miguel, 2015).

Econometric measurement of the benefits of climate policy faces different challenges when compared to air pollution or ecosystem services policies. An abundance of high-frequency inter-temporal variation in climatic variables (i.e. weather) is plausibly exogenous (see e.g., Deschênes and Greenstone (2007) and Schlenker and Roberts (2009a)), but utilizing this variation to compute economic impacts of non-marginal climate changes requires some care (Hsiang, 2016). A central empirical challenge has been determining how exposure to the climate can be appropriately measured, then gathering and transforming various climatic data into these measures for integration to econometric models (Auffhammer et al., 2013).

Some cross-sectional patterns in climate exposure

Baseline climatic conditions at present 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 (Gallup, Sachs, and Mellinger, 1999; Hornbeck, 2012b; Nordhaus, 2006; Schlenker, Hanemann, and Fisher, 2006; Hsiang and Jina, 2015). However, since populations might select into different locations based on how their preferences map onto the climatological endowment (Acemoglu, Johnson, and Robinson, 2001; Olmstead and Rhode, 2011; Hornbeck, 2012a; Albouy et al., 2016; Deryugina, Kawano, and Levitt, Forthcoming), it is difficult to measure the causal effect of natural endowments directly.

The possibility of persistent economic effects of endowments has contributed to the general "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; IPCC, 2014; World Bank, 2017; Hallegatte et al., 2015). While it is true that poor populations tend to live in hotter

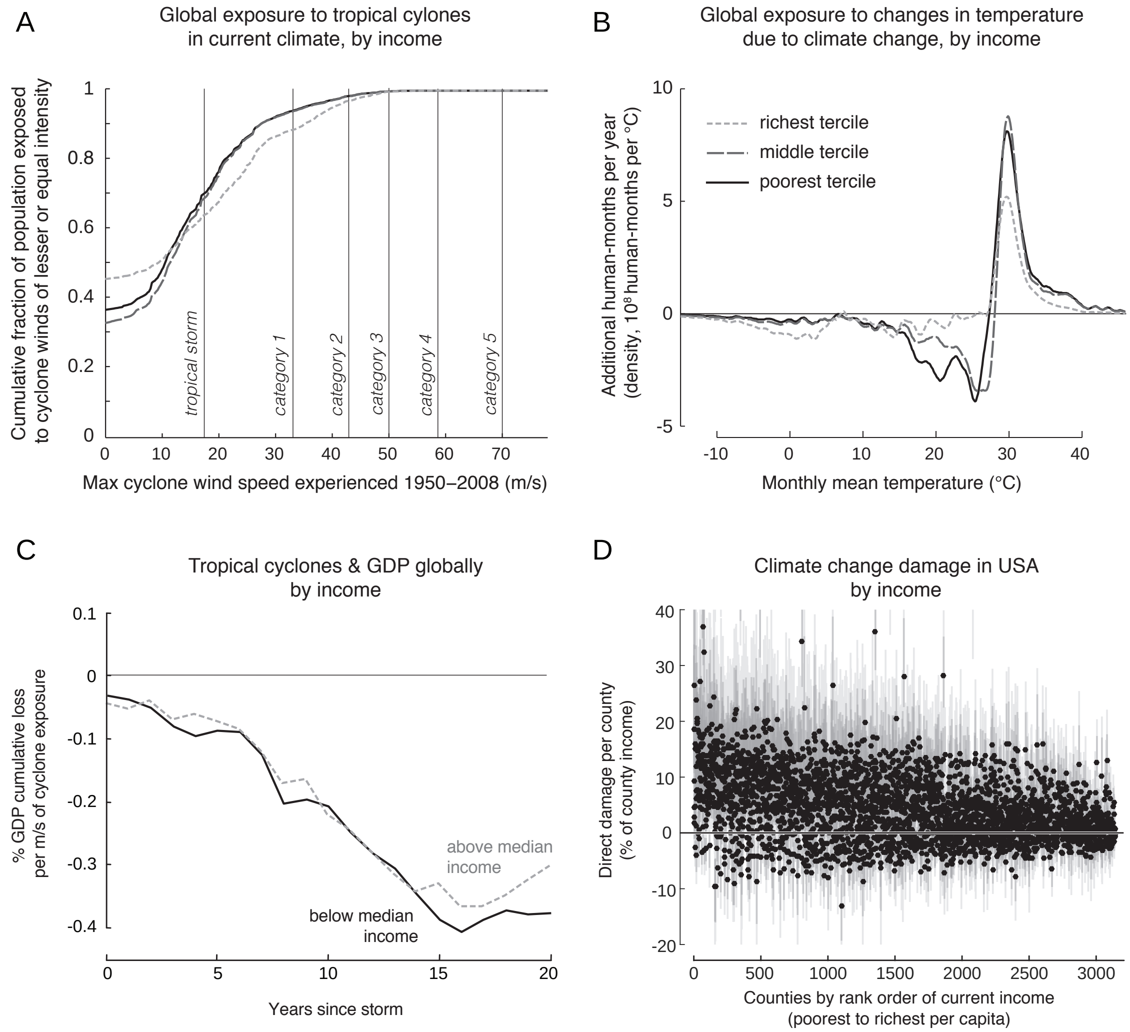

Figure 4: (A) Cumulative distribution function for maximum cyclone winds experienced under the current climate for populations in terciles of the global income distribution (2000 est.): dotted=richest, dashed=middle, solid=poorest. Vertical lines indicate threshold maximum wind speeds on the Saffir-Simpson cyclone intensity scale (maximum value in sample is 78 m/s). Based on authors' calculations using data from CIESIN (2005); Sala-i Martin (2006); Hsiang and Narita (2012). (B) Change in the expected distribution of monthly temperatures experienced by the global population due to business as usual warming by 2100. Based on authors' calculation using data from Meehl et al. (2007); income terciles are the same as in (A). Negative values indicate fewer months at a corresponding temperature, positive values indicate more moths at a corresponding temperature. (C) Homogeneous marginal damages on GDP per capita growth (1970-2008) from one additional m/s of national average cyclone exposure for rich and poor countries; from Hsiang and Jina (2014). (D) Probabilistic projections of direct economic damage from business-as-usual warming (RCP8.5) by 2080-2099 for US counties ranked by their current incomes; from Hsiang et al. (2017). Circles are median estimates, dark whiskers are inner 67% of probability mass for each county, light whiskers are inner 90% of probability mass.

and drier locations, both within and across countries (Nordhaus, 2006; Park et al., 2015), there are notable exceptions 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). Furthermore, some evidence suggests this cross-sectional association has changed over time (Acemoglu, Johnson, and Robinson, 2002). Tropical countries, which tend to be poor, are the most exposed to the El Niño Southern Oscillation (ENSO) (Hsiang and Meng, 2015), although wealthy Australia is notoriously heavily exposed as well (Nicholls, 1989). Tropical cyclones (the class of phenomena including hurricanes, typhoons and tropical storms) tend to move away from the equator for physical reasons and their baseline distribution across space is spread fairly evenly across global income categories—we show this in the cumulative distribution function in Figure 4A, which we compute by overlaying the global cyclone climatology from Hsiang and Narita (2012) on the global pixel-level population distribution (CIESIN, 2005) sorted by their estimated location in the global income distribution from Sala-i Martin (2006). Roughly 35% of the two poorer terciles are never exposed to a tropical cyclones, whereas 45% of the richest tercile is never exposed. However, this high-income advantage reverses when the intensity of cyclones is considered: a relatively larger fraction of the rich tercile is exposed to tropical cyclone winds of any intensity above those equal to "tropical storm" status (according to the Saffir-Simpson intensity scale). Current tornado climatologies represent perhaps the most extreme counter-example of standard intuition: because the strong temperature and pressure gradients required to generate tornadoes only exist over land in the middle latitudes, tornado exposure is almost exclusive to populations that are relatively wealthy (US, Europe, and Australia) or middle income (South Africa, Argentina, and China) (Goliger and Milford, 1998).

The projected distribution of exposure to future climate changes with little or no mitigation is also more complex than the simple notion that poor countries will face the largest quantities of adverse exposure. There is negative correlation between current average income and the magnitude of future average temperature changes across locations, and little correlation between income and rainfall changes. Average temperature changes (Δe_i in the sense of Figure 1) are expected to be most extreme in northern locations, which tend to be wealthier today, and lowest in the tropics (Stocker, 2014; Hsiang and Sobel, 2016). However, changes in exposure to extremely hot temperatures (e.g., $> 30°C$), which are often thought to be the most damaging events, will be largest for the poorest populations around the world. This is shown in Figure 4B, which shows the *difference* between the probability distribution of temperature exposure in 2080-2099 under warming relative to the present.

These differences show how the expected experience of an individual drawn at random, from the global income terciles computed above, change with warming. The largest positive change occurs for poor and middle income terciles above $> 29°C$, indicating that these individuals will experience many more days at these very high temperatures.

Changes in future rainfall are substantially less certain and more mixed with no clear association with current income (Stocker, 2014), since the deep tropics and high latitudes get wetter while subtropics tend to dry out. Changes in future tropical cyclone distributions are similarly unrelated to current incomes, with the strongest intensification expected in the East Asia, weakening in the Indian ocean, and unclear changes in the Atlantic (Knutson et al., 2010). Thus, overall, there is little support for the notion that exposure to future climate changes are inherently greater for poorer populations. However, once one accounts for the potentially heterogeneous marginal effects of these changes, future damages seem likely to be larger for poor populations.

Identifying heterogeneous marginal effects of climate

Dose-responses from climatic conditions are usually compared among contemporaries across different locations, such as vulnerability across different 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 examining contemporaries, the core question is usually either (i) whether some social or economic attribute of a population, such as higher income and stronger institutions (e.g., Dell, Jones, and Olken (2012)), cause them to suffer larger or smaller responses from climatic exposure, or (ii) whether populations more regularly exposed to a specific type of climate are better equipped to cope with the type of events characteristic of that climate (e.g., Hsiang and Narita (2012)). In this second case, the intuition is that if populations experience a climatic event more frequently, they may have learned about that event and invested in precautions that will limit their losses each time the event occurs. A similar intuition holds when examining how marginal effects evolve with time, since populations may gradually learn about their climate and then develop and deploy technologies to cope with specific events they expect to occur, causing their marginal losses to gradually decrease. All of these comparisons are primarily descriptive and cannot usually be interpreted as causal, since there is not exogenous variation in those factors that might be determinants of vulnerability. However, Hsiang, Burke, and Miguel (2013) point out that in some contexts a potential cause of vulnerability could be credibly identified (or ruled out) if some exogenous change causes a key channel to appear for the first time or to be abruptly obstructed if it was already present, and a corresponding sharp change (or absence of change) in marginal losses is observed at that moment. Some recent examples of this approach include the demonstration that work-for-pay programs in India reduce the sensitivity of local violence to rainfall (Fetzer, 2014) and the sensitivity of child test scores to temperature (Garg, Jagani, and Taraz, 2017). Also, Sarsons (2015) shows that access to dams does not alter the rainfall-violence link in India. Hornbeck and Keskin (2014) found that new irrigation technologies reduced US farmers' sensitivity to drought when they also had access to a major aquifer, and Barreca et al. (2016) provide evidence that the introduction and deployment of air-conditioning technologies reduced the marginal impact of temperature on mortality in the US.

In many cases where dose-responses are observed to differ significantly across populations, economic explanations may be consistent with these patterns. For example, Hsiang and Narita (2012) show how high spatial concentration of capital in rich countries may lead to higher defensive investment and lower responsiveness from cyclones, and Davis and Gertler (2015) demonstrate patterns of climate-related energy demand may reflect the influence of income on air-conditioning demand. Some patterns of heterogeneity suggest the existence of additional market failures. Credit constraints likely bind in many lower income contexts, causing individuals to under-invest in protective measures (Burgess et al., 2011) or adopt *ex-post* coping strategies that may be effective in the short run but extremely costly in the long run, such as disinvesting in children (Maccini and Yang, 2009; Anttila-Hughes and Hsiang, 2011) or engaging in transactional sex (Burke, Gong, and Jones, 2015).

In numerous cases, as documented by Carleton and Hsiang (2016), dose-response functions are similar between low and high income countries. For example, a frequent observation is that rich and poor populations respond to certain types of climate exposure with similar marginal losses, when one might expect wealthy populations to be more adapted and thus exhibit lower climate sensitivity. For example, Figure 4C displays the long-run effect of tropical cyclones on GDP growth from Hsiang and Jina (2014), where relative income losses per unit of exposure for rich and poor countries appear to be almost identical. Understanding why such adaptation gaps persist in some cases and not others is an important challenge for future research.

Other than looking at the role of income, another line of inquiry is to ask whether learning shapes marginal effects by comparing dose-response functions from short-lived vs. gradual changes (Dell, Jones, and Olken, 2012; Burke, Emerick et al., 2016). This class of analysis attempts to determine whether observed differences in responsivness within a population are due to experience and subsequent adaptation; the hope is that such insight might also explain differences in climate sensitivity across populations. The motivation for this comparison is the intuition that if populations can endogenously alter their sensitivity through learning and adaptation in the long run, the marginal effects of slow climate changes should be less damaging than those of unexpected short-lived events (Shrader, 2016). However, if the observed marginal effects are similar across these cases, that may suggest limited scope for effective adaptations (Moore and Lobell, 2014). A continuous version of this approach is to filter time series or panel data at all temporal frequencies and estimate climate sensitivity at each frequency of climatic variation (Hsiang, 2016). Despite these efforts, the literature has had limited success pinning down systematic patterns for the relationship between climate sensitivity at short and long time scales.

Separate from any notion of adaptation, another major source of heterogeneity in climate sensitivity stem from nonlinearities in the dose-response function—a relationship that may be more mechanical in nature than indicative of deeper economic dynamics. Nonlinear responses to climate have been carefully identified in a number of contexts, whether examining effects of climate on crop yields (Schlenker and Roberts, 2009b; 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, forthcoming), human capital formation (Park, 2017), or income (Deryugina and Hsiang, 2014; Isen, Rossin-Slater, and Walker, 2017). In these cases, the baseline climate of a population may play a large role in determining the marginal damages from climate simply because the population's initial position on the dose-response function may exhibit a steeper or shallower slope. Burke, Hsiang, and Miguel (2015) demonstrate the importance of this issue by showing that a nonlinear relationship between temperature and economic growth appears statistically similar to a situation where poor countries have large negative marginal effects of temperature because they are poor (i.e. because poor countries are also systematically hotter than rich countries). However, the economic projections (or counterfactuals) under global warming differ dramatically depending on whether heterogeneity is assumed to be caused by income or by non-linear temperature responses. Frequently, the strong correlation between the economic characteristics of populations and their baseline climates makes it exceptionally challenging to determine which drives heterogeneity in marginal damages. Furthermore, it is also possible that these nonlinear dose-response functions strengthen differences in baseline economic characteristics. For example Hsiang et al. (2017), demonstrate that strong nonlinearities in dose-response functions lead to a highly regressive distribution of climate change damages across counties in the US (see e.g., Figure 4D), likely increasing pre-existing patterns of economic inequality.

Some policy considerations concerning climate change

One of the most important questions arising from these findings is to understand how large populations respond and (possibly) reorganize in response to such uneven exposure and damages from climate change—and what policy-makers should do in response. Labor may respond to changes in local productivities induced by the climate by migrating (Hornbeck, 2012a; Feng, Oppenheimer, and Schlenker, 2012; Colmer, 2016). If climate damages are largest in poorer locations then labor movement to richer locations could reduce the regressive impacts of climate. However, pre-existing barriers to labor mobility may prevent equalization of marginal labor productivity across locations (Desmet, Nagy, and Rossi-Hansberg, 2015; Missirian, Schlenker et al., 2017), and climate changes may directly affect the feasibility of migration in the presence of credit constraints (Kleemans and Magruder, Forthcoming). Adjustments in trading patterns could also partially alleviate some uneven impacts of climate (Jones and Olken, 2010; Costinot, Donaldson, and Smith, 2016), but large-scale patterns of unequal damages could potentially be worsened by trade (Newbery and Stiglitz, 1984; Dingel, Hsiang, and Meng, 2017).

Perhaps the more concerning possibility is that large-scale uneven impacts of climate change may destabilize existing institutional arrangements, increase incentives to violently redistribute wealth, or generate other forms of social conflict (Hsiang, Burke, and Miguel, 2013; Axbard, 2016; Obradovich, 2017). A large number of historical analyses suggest that conflict and the breakdown of social order are regular responses to the large-scale reorganization of climate-related wealth (Kuper and Kröpelin, 2006; Yancheva et al., 2007; Haug et al., 2003; Bai and Kung, 2010; Chaney, 2013), but little is known about the modern risk of these outcomes, how to prevent them through policy, or optimal responses to these types of events once they are underway. Understanding the extent of this risk, and how it might be managed, seems an important area for future research.

Discussion

There exists tremendous heterogeneity in exposure to environmental externalities at both a local and global level. This heterogeneity has led researchers to question whether some populations disproportionately bear the burden of environmental damages, with substantial concern that poor populations are differentially harmed. Recent econometric work has clarified some cases in which this is true and others in which the data run counter to this intuition. A pervasive difficulty in the interpretation of previous literature that documents heterogeneity in dose-response functions by income is that, in many cases, it remains unclear whether the heterogeneity stems from differences in exposure levels or differences in the structure of the response function across populations. The possible presence of nonlinear response functions and non-uniform exposure complicates the determination of whether marginal damages fundamentally differ across groups, especially when exogenous variation in factors that might affect responsiveness is absent. Understanding the underlying source of heterogeneity in dose-response functions is important to understand the benefits of future policy decisions. We see the investigation into the underlying causal determinants of heterogeneity in dose-response functions as being a key research area going forward.

A second difficulty that often arises in this literature is translating damages measured in physical quantities, such as "number of deaths" or "acres of forest cleared," into welfare measures that may be compared across contexts and outcomes. This is especially true when there are unobserved tradeoffs made by individuals in a market equilibrium, which may implicitly compensate individuals for their willingness to tolerate increased exposures and/or risk (Rosen, 1974). In some cases, researchers have turned to hedonic approaches that deliver results which can be interpreted in welfare terms under some assumptions. In other cases, researchers assign standardized valuations to physical quantities, such as valuing statistical lives, although such valuations may not always be well identified or grounded in empirical observations. Despite these efforts, it is widely understood that these solutions are incomplete and/or not universally applicable. Thus, developing robust and generalizable approaches for recovering empirical welfare measures of non-market amenities is currently a core frontier problem in understanding the distribution of environmental damages.

We close by posing a challenge to researchers. The finding that poor populations, in many contexts, might be differentially exposed or impacted by environmental conditions suggests one of the most difficult but (potentially) important unanswered questions in this research space: Do any environmental damages have impacts long-lasting enough to generate persistent feedback loops? For example, if being poorer causes households to suffer relatively larger losses from the environment, then can this damage in turn cause that household to be poorer and suffer larger losses yet again in the next generation? Such feedbacks would be important to identify, since they may give rise to long-run compounding distributional consequences with potentially large welfare implications. Compelling empirical evidence of any such a feedback loop is lacking, but there exist some cases where cross-sectional—and possibly long-run—patterns are similar in sign or structure to the short-run effects that the empirical literature has mostly focused on. For example, nonlinear cross-sectional distributions of income across temperatures (Nordhaus, 2006) are broadly consistent with short-run effects of temperature on income growth (Burke, Hsiang, and Miguel, 2015). Similarly, some of the most impoverished regions of the United States are areas with the highest levels of ambient air pollution (Spira-Cohen et al., 2010, 2011). However, in both cases, it remains completely unknown if any of these observed cross-sectional relationships match the short-run evidence coincidentally or causally. Could environmental factors be a key driver for the distribution of wealth we observe in the world today? Credibly identifying such long-run effects will likely require that we deeply understand the long-run dynamic response to environmental conditions, a problem that we believe is the most valuable target for future inquiry.

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