How General Are Environmental Externalities?*

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Abstract

How does accounting for a broad set of environmental externalities change answers to important economic questions? Many papers study a single externality. I analyze spatial data on air pollution, drinking water pollution, surface water pollution, extreme temperatures, floods, and wildfires. Two conclusions emerge. First, correlations across externalities are low, sometimes negative, limiting generalizability. Economic and geophysical fundamentals help explain the divergent patterns. Second, answers to important economic questions do not readily generalize across externalities. The Great Recession did not improve all environmental quality; it improved air pollution. Spatial patterns of growth are increasing exposure to extreme heat but decreasing exposure to other externalities. Poor communities do have higher exposure to all externalities, but Black and Hispanic communities do not. A spatial equilibrium model finds that these externalities have costs exceeding 2 percent of GDP in most counties and account for over 10 percent of population in many counties, though patterns vary dramatically across externalities. Overall, analyzing a single externality can provide inaccurate conclusions about broad environmental quality.

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1 Introduction

Many analyses in environmental economics scrutinize a single externality. Do such analyses obtain general findings about the environment and the economy, or do they instead reflect the idiosyncratic pattern of the environmental good that a specific study analyzes? How does accounting for a broad set of environmental externalities change answers to important economic questions?

Many papers suggest that the analysis of a single externality generalizes to broader environmental quality. Kahn (1999), for example, concludes his analysis of particulate air pollution in early 1980s recession, "[O]ne silver lining of reduced manufacturing activity is improved environmental quality." Currie, Voorheis and Walker (2023)'s study of air pollution and inequality summarizes, "The analysis confirms that African Americans tend to live in the most polluted areas nationally." Boomhower, Fowlie and Plantinga (2023)'s analysis of wildfires concludes, "One form of adaptation is to move populations out of harm's way. To date, development pressures and a shortage of affordable housing have moved people in the opposite direction."

Understanding whether analysis of one externality generalizes helps obtain accurate answers to important questions about recessions, inequality, population growth, and other economic topics. Such an understanding can also provide useful insights to spatial economics. Classic and quantitative spatial equilibrium models study the value of local amenities across regions (Roback 1982; Redding and Rossi-Hansberg 2017). Many studies project model-based estimates of amenities on one or two environmental goods. How effectively do such analyses generalize to characterize the environmental amenity value of Los Angeles, Miami, or other regions?

I compile mean levels of six environmental externalities for each US county and year: air pollution, drinking water pollution, surface water pollution, floods, heat, and wildfires.[1] The first three are pollution; the last three are natural hazards.

I use these data to pursue two broad objectives. First, I study spatial and temporal correlations across externalities. Do regions and years with high levels of one externality have high levels of others? Finding high correlations suggests that analysis of one externality is more likely to generalize. For example, if the regions with high levels of air pollution also

[1]For convenience I describe these all as externalities, though some sources are non-anthropogenic. For example, many floods and wildfires would likely occur independently of human activity.

have extreme heat, then analysis of air pollution is more likely to obtain conclusions that also apply to high temperatures. To understand drivers of these correlations, I discuss how population density and geophysical fundamentals drive different patterns across externalities.

Ex ante information suggests the prior that correlations across externalities may be systematically positive, so economic analysis of one externality may generalize well. In part, this is because some externalities cause others. For example, pollution in surface water causes polluted drinking water, and heat exacerbates surface water pollution and wildfires. Additionally, one source can cause many of these externalities. Electricity generation and transmission, for example, directly cause air and water pollution, wildfire ignitions, and urban heat islands. To give another example, environmental research argues that climate change creates "compound risks" combining many externalities (Ayanlade et al. 2023; Simpson et al. 2023).

I find that this prior is generally incorrect. I estimate modest correlations across externalities. The mean cross-sectional correlation is 0.05, and the mean longitudinal correlation across externalities is -0.01. Some correlations are large and positive, others are large and negative. These correlations are low partly because different externalities have different drivers. For example, drinking water pollution and wildfire risk predominantly occur in low-density areas, while air pollution, flood risk, and extreme heat predominantly occur in high-density areas. In another example, terrain ruggedness increases air pollution by trapping it, but decreases water pollution since higher velocity streams abate organic pollution.

The paper's other broad objective is to revisit classic economic questions using a broad set of externalities. I find that answers to classic economic questions do not typically generalize well across externalities, and that accounting for a broad set of externalities changes answers to important economic questions. I first ask how recessions affect environmental quality. I find that while the Great Recession decreased air pollution, it had no impact on other externalities, and I reject the hypothesis of economically large magnitudes. I interpret that a relatively large share of air pollution comes from contemporaneous industrial production, and a smaller share of other externalities do.

How do spatial patterns of population and housing growth affect exposure to externalities? Although population trends are increasing mean exposures to extreme heat, they are decreasing mean exposures to drinking water pollution and floods. I interpret that people are primarily moving to locations with broad amenities and elastic housing supply, which

are correlated positively with some externalities but negatively with others.

How unequal are environmental exposures across demographic groups? While some patterns are general, many others are not. Poor communities have greater exposures to essentially all the externalities I study. Black and Hispanic communities have greater exposure to some but not others. The strongest relationship I find, which is also the one other papers study most, is that Black communities experience higher air pollution rates. As one comparison, Hispanic communities face substantially lower air pollution rates.

How do externalities change the spatial distribution of population and income? How do externalities change the spatial distribution of population and income? Turning off externalities increases welfare by over 2% in most counties and results in the movement of at least 11 million Americans across the US. At the same time, changing these externalities has disparate effects on the spatial structure of population and housing. Coastal areas benefit least, despite their flood exposure, because externalities concentrated inland have larger costs.

This paper builds on several literatures. It provides the first joint economic analysis of this broad set of environmental externalities across space and time. Some papers compare several pollutants for a single category of externality. For example, Bell et al. (2004) study how ozone and particulate matter air pollution affect health; Muller and Mendelsohn (2009) analyze spatially heterogeneous willingness to pay for many air pollutants; and Keiser et al. (2023) analyze many drinking water pollutants. Other studies compare two categories of externalities. Greenstone (2003) and Gibson (2019) compare emissions of air and surface water pollution. Keiser and Shapiro (2019) relate temperature to surface water pollution and Graff Zivin et al. (2023) link air pollution and influenza. Review articles discuss papers on various externalities (e.g., Banzhaf, Ma and Timmins 2019; Copeland, Shapiro and Taylor 2022; Balboni and Shapiro 2025).

Several non-academic projects assemble data on multiple hazards. Two government databases have undertaken related data collection—the USEPA (2025*c*)'s EJScreen database and FEMA (2025)'s National Risk Index. First Street Foundation (2025) aggregate costs for several climate-related hazards. I do not believe analysis has studied correlation structures across all these externalities or their implications for the economic questions I study. My approach resonates with the White House (2023) Environmental and Economic Statistics initiative, which seeks to incorporate many environmental goods including air and surface water quality into national accounts.

I also build on analysis of economic questions for individual externalities. Many papers find that air pollution reflects the business cycle, including the early 1980s recession, the Great Recession, and COVID-19 lockdowns (Kahn 1999; Chay and Greenstone 2003; Davis 2012; Heutel and Ruhm 2016; Tong et al. 2016; Venter et al. 2020; Finkelstein et al. 2024). I do not believe research has investigated how recessions affect the other externalities I study, though I discuss possible mechanisms for such effects. The Environmental Kuznets Curve literature (Grossman and Krueger 1994; Copeland and Taylor 1994) provides international comparisons of how environmental quality relates to income per capita, though typically not to recessions. Several sources find that US housing development is moving towards areas with greater wildfire exposures and extreme heat (Deschenes and Moretti 2009; Radeloff et al. 2018; Boomhower 2023; Boomhower, Fowlie and Plantinga 2023; Radeloff et al. 2023).Many studies note that low-income and minority communities have greater exposure to air pollution and some other externalities, and examine how policy affects the distribution of exposures (Currie 2011; Fowlie, Holland and Mansur 2012; Currie et al. 2015; Grainger and Ruangmas 2018; Hsiang, Oliva and Walker 2019). Many spatial models compare regional amenities to one or two environmental variables, typically mean temperatures or air pollution (Roback 1982; Albouy 2016; Diamond 2016).

Three challenges help explain why existing research focuses on individual externalities. Data on some externalities are challenging to access. Drinking and surface water pollution data are not widely analyzed or available, measures of flood risk are rapidly evolving, inferring willingness to pay for these externalities requires careful analysis, and assembling comparable spatial measures of all these externalities is complex. Additionally, publication bias may lead to a concentration of research on externalities with large impacts. The preponderance of research on air pollution or extreme heat for certain questions could be because analysis finds clear impacts for these outcomes. Finally, it is not obvious which externalities analysis should cover. This paper seeks to make progress on these challenges. One goal is to compile and share data on many externalities in a common spatial format, to decrease the barriers to analyzing them. For the last two challenges, I argue that the externalities I study are important, easily measured, and broadly relevant.

More generally, I provide an environmental application of the broader external validity question of how well parameter estimates extrapolate across domains. Environmental economists sometimes question the use of valuation estimates from one setting for the same

pollutant in different settings ("benefits transfer," e.g., Bergstrom and Taylor 2006). My analysis echoes the assessment of parameters like risk aversion from one domain extrapolate to others (Barseghyan, Prince and Teitelbaum 2011; Einav et al. 2012).

The paper proceeds as follows. Section 2 describes the data. Section 3 discuss correlations across externalities and explanations. Sections 4 through 7 revisits important economic questions. Section 8 concludes.

2 Data

2.1 Externalities

For each externality, I calculate levels for the mean person in each county×year; ongoing work is constructing data at finer geographic resolution. I study the years 2003-2019 or the subset of years a particular dataset covers. Ongoing extensions cover through 2024, particularly to reflect recent wildfire trends (Burke et al. 2021). I report both cross-sectional analyses that average across years within each county and panel data estimates. Sensitivity analyses in the appendix consider alternative data sources and some individual pollutants. I use the most accurate or comprehensive data source I can identify for each externality, and other data sources for sensitivity analyses. This section describes the main sources; Appendix A provides details. Most tables and figures analyze each externality in physical units, though in some cases I report elasticities or beta coefficients when this facilitates comparisons across externalities or interpretability. I calculate marginal willingness to pay for most externalities, though ongoing work is incorporating willingness to pay for water pollution.

I primarily measure air pollution from the ambient concentration of particulate matter smaller than 2.5 micrometers ($PM_{2.5}$) in $\mu g/m^3$, using remote sensing data (Van Donkelaar et al. 2016; Center For International Earth Science Information Network-CIESIN-Columbia University 2022; Berry 2024). I estimate the willingness-to-pay for clean air using four inputs: I multiply a leading estimate of how pollution affects mortality (Krewski et al. 2009) by the Environmental Protection Agency's estimate of the value of a statistical life; I calculate the life expectancy for each age group from life tables (Arias, Xu and Kochanek 2023); and I scale the relative life expectancy of people who die from environmental externalities (Deryugina et al. 2019). I measure the marginal willingness to pay using adult mortality since it accounts

for the vast majority of particulate matter's estimated damages (USEPA 2009; Tschofen, Azevedo and Muller 2019). Sensitivity analyses study ground-based pollution monitors for $PM_{2.5}$ (USEPA 2025*a*) and surface ozone pollution (Requia et al. 2020*a*,*b*).

I primarily measure drinking water pollution using 50 million readings from 48 states that individual drinking water systems report to state environmental agencies. Keiser et al. (2023) collect and harmonize these data. I measure the share of readings exceeding current health standards set under the Safe Drinking Water Act. I average values across pollutants within the five main categories of drinking water pollution (microorganisms, disinfection byproducts, inorganic chemicals, organic chemicals, and radionuclides), then weight each of the five categories equally. Sensitivity analyses discuss federally-reported violations, from Envirofacts (2020).

I primarily measure surface water pollution using readings from the National Water Quality Portal (National Water Quality Monitoring Council 2024). For each county×year, I count the share of readings that are unsafe for fishing, a common omnibus water quality measure that aggregates several underlying physical pollutants (Keiser and Shapiro 2019). Sensitivity analyses discuss dissolved oxygen deficits (USEPA 2025*b*).

I primarily measure extreme temperatures as the days per county×year where mean temperature falls below 40°F or exceeds 80°F. I obtain data from PRISM (2025) and calculate an unweighted mean across locations within a county×year. Sensitivity analyses consider heating and cooling degree days. I estimate effects of extreme heat on premature mortality using estimates from (Barreca et al. 2016), again multiplying them by the value of a statistical life, scaled by the relative life expectancy of people who die from environmental externalities (Deryugina et al. 2019).

I primarily measure expected flood costs from the mean cost of flood insurance under RR2.0, which is believed to represent mean costs (previous versions of flood insurance were better than actuarially fair). Sensitivity analyses discuss the number of Presidential Declared Disaster floods and extreme storms with flooding, and a flood risk index from a leading industry firm, First Street Foundation.

I measure expected wildfire costs using estimates of expected risk from the US Department of Agriculture (Scott 2025). This source calculates expected risk as the probability that a wildfire burns a site times expected wildfire intensity, then averages risk across housing units within a county. To calculate county willingness-to-pay for fire risk, I multiply this

mean expected risk, the number of housing units in the county, and the average home value.

Appendix Table 1 presents summary statistics, years available, and data sources. Panel A shows that each externality varies substantially across counties. For $PM_{2.5}$, the 95th percentile of the distribution has nearly three times the concentration as the 5th percentile; for wildfire damages, this ratio is 700 times. Panel B shows that externalities also vary widely within a county and over time. For example, the within-country standard deviation of most externalities in Panel B has similar order of magnitude to the cross-sectional cross-county standard deviation of externalities in Panel A. For air pollution, the cross-sectional variation is slightly larger; for drinking water pollution, and floods, the longitudinal variation is slightly larger.

I incorporate several other data sources. To analyze population and economic density, I use population data from National Historical Geographic Information System (2024), records of each county's land area from National Historical Geographic Information System (2023), and county GDP from Bureau of Economic Analysis (2024). I use these population data, and counts of the number of housing units by county×year from National Historical Geographic Information System (2024) to analyze patterns of population and housing unit growth. To study the Great Recession, I use county×year unemployment data from Bureau of Labor Statistics (2023). To study demographics, I measure the share of each county that is Black and Hispanic from National Cancer Institute (2024), and the share with income below the poverty line with data from the 2010 Population Census (Census Bureau 2025).

3 Correlations Across Externalities

3.1 Maps of Externalities

Each map in Figure 1 shows the mean value of one externality across counties. Severe levels appear in dark blue, moderate levels in medium blue, and modest levels in light blue. Areas in white lack data.

Figure 1 reveals extremely different spatial patterns across externalities. These patterns preview the paper's first broad finding of low correlations across externalities. In Panel A, particulate matter air pollution has high levels in the East and California. In Panels B and C, drinking and surface water pollution have broader geographic dispersion. In Panel D,

flood risk is greatest in the Atlantic and Gulf coasts, the Mississippi Valley, and Appalachia. In Panel E, heat is concentrated across the Sun Belt in the South and mid-Atlantic. In Panel F, wildfires are concentrated in the West. Many though not all sensitivity analyses in Appendix Figure 1 echo these spatial patterns. They do underscore the finding that spatial patterns from one externality do not generalize well to others.

Some spatial patterns in Figure 1 have intuitive explanations. Air pollution has higher concentrations in the East due to high population density and the geographic concentration of coal-fired power plants in the East, and because prevailing winds blow to the East. The South has more extreme heat due to its lower latitude. The West has more wildfires due to its low precipitation, low humidity, and high windspeeds (Patel 2018). The Atlantic coast and Mississipi Valley flood since they have flat, low-lying areas with abundant precipitation. Appendix B.1 discusses further details.

Another interesting comparison across externalities involves spatial autocorrelation. Air pollution and heat have high spatial autocorrelation. For example, counties with high levels of particulate matter tend to have neighboring counties with high particulate matter levels. Heat has even more spatially smooth patterns. Wildfire risk has moderate spatial autocorrelation. In contrast, drinking water pollution, surface water pollution, and flood risk have much less spatial autocorrelation. In many cases, one county has extreme levels of these externalities but a neighboring county has little to none. Appendix Figure 1 shows that these patterns persist in the sensitivity analyses using alternative data sources, which makes these patterns more likely to reflect true underlying features of the world. Ongoing work calculates Moran's I for each externality, a common metric of spatial autocorrelation.

Two reasons explain why different externalities have different degrees of spatial autocorrelation. First, different forces move these externalities. Wind smoothly mixes air pollution and heat across neighboring counties. The externalities with the greatest spatial autocorrelation are most transmitted by wind. Surface and drinking water pollution and fire move primarily through terrestrial patterns (water flow and combustion), which are more spatially idiosyncratic. Second, these externalities have different underlying origins. Heat comes from solar radiation, which is greatest at lower latitudes, so varies smoothly over space. Wildfire risk reflects moisture, which is lower west of the 100th meridian. Drinking water pollution, in contrast, depends on treatment effectiveness in different public water systems, which vary by town.

I am not aware of prior discussions of the spatial smoothness of externalities, but it could matter for a few reasons. Because migration costs increase in distance, spatially autocorrelated externalities may be more costly to avoid, as people and firms travel further to avoid the externality. A migrant can reach low levels of an externality with low spatial autocorrelation by traveling to a nearby county. Spatial autocorrelation also suggests an externality may have more local sources and control. For example, a city can decrease its own drinking water pollution by investing in drinking water treatment, but a city cannot decrease its temperature by slowing climate change.

3.2 Correlation Across Externalities

Each panel in Table 1 lists the three counties with the highest values of one externality, shown in bold. Each row lists that county's values for all externalities.

Table 1 reveals several informative patterns. No county in Table 1 appears in multiple panels, implying that a county has the worst environmental problem for only one externality. Additionally, no county in Table 1 is in the central part of a major metro area.

Many specific patterns in Table 1 are also sensible. Ottawa County, Ohio, with high air pollution, is near the industrial centers of Toledo and Cleveland, and somewhat downwind of the coal-abundant Ohio River Valley. Loop County, Nebraska, has high arsenic concentrations in drinking water (Nebraska AWWA 2025). Lee County, Texas, has surface water pollution problems due to dissolved oxygen shortages, partly reflecting nutrients and high temperatures. Flood risk in Cameron Parish, Louisiana, covers its low-lying towns that abut the Gulf of Mexico (Coastal Protection and Restoration Authority 2025). Starr County, Texas, experiences frequent extreme heat as one of America's furthest south counties. Elko County, Nevada, has many lighting-sparked wildfires (Resource Concepts 2005).

Table 2 shows pairwise correlations across externalities. Panel A reaffirms this section's main finding: correlations across externalities are small, sometimes negative. Across all pairwise comparisons, the mean correlation is -0.002. Heat and floods do have a high correlation of 0.33, partly since both are concentrated in the South, but air pollution and drinking water pollution have a correlation of -0.09. Even relationships with a physical basis are modest. Pollution in surface water directly causes pollution in drinking water. Surface water and drinking water pollution have a correlation of 0.01, however, not statistically distinct from zero, perhaps because drinking water pollution most reflects treatment failures rather than

surface water pollution. Heat and wildfires have a correlation of only 0.02. Again, although heat drives wildfires, wind, aridity, and steep topography matter more, and heat concentrates in the South while wildfires concentrate in the West. Appendix Table 3 finds similar patterns in alternative data sources; Appendix B.2 discusses these estimates.

Table 2, Panel B, reports correlations across externalities after residualizing county fixed effects and year fixed effects. These correlations assess whether areas experiencing a high value of an externality of one type in a given year also have a high value of another externality of the same type in a given year. In these residualized data, the mean correlation across externalities is 0.003. Again some correlations are small and positive, others small and negative. Overall, places with a high value of an externality in one year are no more likely to have a high value of other externalities in that year.

3.3 Population Density and Correlations Across Externalities

Why do different externalities have such different patterns? Table 3 provides one simple explanation. It examines the extent to which the density of human and economic activity predict differing patterns across externalities. Panels A and B examine population per square mile and panels C and D examine GDP per square mile. Panels B and D add state fixed effects. Each column analyzes a different externality.

Table 3 shows that population and economic density associate with dramatically different patterns across externalities. Air and drinking water pollution provide an informative contrast. Counties with greater density have substantially higher air pollution, with a semi-elasticity between 0.3 and 0.8. Counties with greater density have substantially lower drinking water pollution, however, with a semi-elasticity of around -0.3. These opposite signs may occur because human and economic activity like driving, heating, and producing goods and services generate air pollution. Drinking water pollution, by contrast, depends more on drinking water treatment, which has increasing returns that benefit systems serving denser populations. Additionally, the US Safe Drinking Water Act imposes tighter standards for systems serving larger populations (Keiser et al. 2023). Figure 2 echoes these findings graphically.

Table 3 shows more complex patterns between density and other externalities. Surface water pollution has similar concentrations across counties with high and low density, perhaps in part because it comes from both agricultural runoff (common in low density areas) and

urban sewage and industrial activity (common in high density areas). The relationship of floods to density depends on the exact measure and controls. Hotter counties have greater density, reflecting migration to the Sun Belt. Counties with wildfires have lower density, as wildfires are common in the low density West. Although wildfires in densely populated areas like the January 2025 Los Angeles fires receive disproportionate public attention, wildfires in sparsely populated areas are more common.

Geophysical fundamentals also drive differential patterns across externalities in established ways. For example, steep topographic slopes can increase ambient air pollution concentrations by trapping air pollution in bowl-shaped topography, as in Los Angeles, Denver, Salt Lake City, and California's Central Valley. Steep slopes also accelerate the spread of wildfires. At the same time, steep topography can decrease surface water pollution by increasing flow velocity and turbulence, which promotes aquatic absorption of dissolved oxygen and fosters aerobic bacteria that break down pollution.

Precipitation provides another geophysical force driving opposite-signed patterns across these externalities. Extreme precipitation causes floods, decreases wildfires, and abates air pollution, as raindrops bring airborne pollutants to the ground. Precipitation has ambiguous effects on surface water pollution—it can dilute industrial pollution and sewage in water bodies, which decreases concentrations, but can increase fertilizer and pesticide runoff from agriculture. Additionally, in cities with combined sewer overflow pipes, where stormwater and sewage pipes flow together, heavy rainfall causes untreated wastewater (e.g., raw sewage) to enter surface waters, increasing pollution.

4 Effects of Recessions on Environmental Quality

The remaining sections of this paper investigate how analyzing a broad set of externalities changes answers to important economic questions.

I first examine how recessions affect a broad set of environmental outcomes. Understanding this relationship could help measure the welfare cost of recessions and understand the economic drivers of environmental change. Effects of recessions on water pollution or natural hazards would temper findings from existing research, which interprets environmental benefits of recessions as accruing substantially through air quality.

Several mechanisms could cause recessions to affect several externalities. Recessions de-

crease the scale of economic activity, particularly for air and water-pollution intensive sectors like heavy manufacturing and electricity generation. Recessions could decrease maintenance or investment in water infrastructure, levees, and dams, increasing flooding. Recessions could also slow development of wetlands and construction of impermeable surfaces, decreasing flooding. By slowing energy consumption, recessions could decrease urban heat island effects.[2] Recessions could expand wildfire risks by decreasing funding for firefighters, wildfire detection, maintenance of power lines, and other wildfire mitigation. Effects of recessions on agricultural production, a leading source of water pollution which the Clean Water Act largely does not regulate, and on municipal wastes and runoff, another major pollution source, are unclear.

Following Yagan (2019); Finkelstein et al. (2024), I estimate the effect of the Great Recession on externalities:

$$y_{ct} = \beta S_c 1[t \geq 2007] + \mu_c + \eta_t + \varepsilon_{ct} \tag{1}$$

Here y_{ct} represents a county$\times$ year measure of an environmental externality, S_c indicates whether county c experienced a severe Great Recession shock, and $1[y \geq 2007]$ represents years after the Great Recession. Severe versus mild recessions reflect 2007-2009 deviations from a county's employment trend. The term μ_c represents county fixed effects, which adjust for time-invariant county characteristics, such as mean environmental quality. Similarly, η_t represents year fixed effects, which account for national effects of the recession and national environmental trends, and ε_{ct} represents an idiosyncratic error. The main coefficient of interest, β, represents the mean differential externality in counties experiencing a severe recession, after 2007. I also graph year-by-year effects of the Great Recession:

$$y_{ct} = 1[S_c = 1] \sum_{\tau} \beta_{1,\tau} 1[t = \tau] + 1[S_c = 0] \sum_{\tau} \beta_{0,\tau} 1[t = \tau] + \mu_c + \eta_t + \varepsilon_{ct} \tag{2}$$

Figure 3 plots coefficients from equation (2), representing patterns of environmental externalities around the time of the Great Recession. The solid line in each graph describes counties that experienced a severe recession; the dashed line describes counties that experienced a mild recession. Each graph begins in 2003 and shows outcomes through 2019 or

[2] An urban heat island is where cities have higher temperatures than nearby areas due to impermeable urban infrastructure absorbing heat and energy consumption emitting waste heat.

the latest year available. I normalize values in each graph to average 100 in years before the Great Recession.

Figure 3, Panel A, shows that the Great Recession decreased $PM_{2.5}$ air pollution. Air pollution was declining nationally before the Great Recession, continuing longstanding trends (Shapiro and Walker 2024). Counties with severe and mild recessions had similar $PM_{2.5}$ levels and trends before 2008. Subsequently, air pollution fell by 5 to 10 percent more in severe recession areas than in mild recession areas. This qualitative finding using remote sensing data echoes prior findings from ground-based monitors (Finkelstein et al. 2024).

Figure 3 suggests little effect of the Great Recession on externalities besides air pollution. Panel B shows that severe and mild recession counties had flat drinking water pollution trends in years before the Great Recession. The graph shows similar declines in drinking water pollution in both areas after the recession, which may reflect national investment in pollution control, subsidized loans provided through the Safe Drinking Water Act, or compliance with tightening standards (Keiser et al. 2023). Panel C shows that surface water pollution had a fairly linear but gradual downward trend for both severe and mild recession counties, with a similar jump for both areas in 2007. Panel D shows similar patterns in floods between severe and mild recession areas. Panels E and F show that heat and wildfires have moderate annual volatility, but similar patterns between severe and mild recession regions, both before and after the recession.

Table 4 provides regression analogues to these graphs, estimated using equation (1). These tabular results also indicate that the Great Recession decreased air pollution but not other environmental externalities. Column (1) shows that on average, counties with a severe recession shock had 0.08 $\mu g/m^3$ lower $PM_{2.5}$ air pollution. This magnitude is smaller than the estimate of 0.16 (0.04) from Finkelstein et al. (2024), partly due to differences in ground monitoring versus remote sensing. Columns (2) through (6) find that the Great Recession did not substantially decrease other environmental externalities. Two signs are positive, two are negative, and one estimate is zero. None besides air pollution, however, are statistically distinct from zero. Some of the point estimates do fail to reject modest impacts. For example, I cannot reject the hypothesis that exposure to a severe recession increases or decreases wildfires by up to about 2 percentage points relative to the baseline mean.

Overall, these estimates indicate that recessions do not improve all environmental quality, but primarily improve air quality. This finding gives reason to revisit a common broad

conclusion in existing work, that recessions improve environmental quality overall. Why do recessions primarily impact air pollution but not other externalities? For the natural hazards of floods, extreme temperatures, and wildfires, the likely answer is that the potential channels discussed earlier have insufficient magnitude to substantially drive aggregate patterns. For drinking and surface water pollution, a plausible explanation is that dominant drivers – agricultural fertilizers, and livestock and human wastes – do not substantially move with the business cycle.

5 Are People and Housing Moving Towards Externalities?

Determining whether people and housing are moving towards externalities matters for a few reasons. Even if levels of externalities in each region stay fixed over time, if people move towards regions with higher externalities, that movement would increase population-mean externalities, and therefore their aggregate costs. It could also increase costs of climate change, which magnifies several of these externalities in regions where they are already high. It could also give reason to scrutinize whether distortions in home insurance markets, wildfire mitigation, or other spatial policies cause spatial moral hazard by encouraging relocation to areas with greater externalities. More broadly, interactions of market failures and distortions for externalities and regional labor supply could give reason to reexamine policy in both domains.

Population and housing might be moving towards externalities for several reasons. Amenities and productivity might be correlated with externalities. For example, growing demand to reside in warm climates could increase population in the Sun Belt, increasing population-mean exposure to floods and extreme heat. Alternatively, increasing population exposure to externalities could reflect spatially heterogeneous housing supply elasticities, where regions with elastic supply have elevated exposure to externalities and regions protected from externalities have already been developed. Because it is costly to build housing on steep slopes, and because sloped areas can also trap and increase increase air pollution, spatial patterns of housing supply could push households away from air pollution. Similarly, wetlands and water resources decrease housing supply (Saiz 2010), and locate in flood-prone areas, so

housing supply may move population growth away from floods.

Appendix Table 6 shows regressions of mean levels of each externality on housing supply elasticities from Saiz (2010). Panel A has no additional controls, while panel B adds state fixed effects. Extreme heat is greatest in areas with inelastic housing supply, partly due to steep slopes in the southwest desert and wetlands in the hot southeast. Flood-prone areas have inelastic supply, since floods occur where water settles and since abundant water decreases the elasticity of housing supply. Nationally, air pollution is greatest in the more elastic housing supply of the industrial Midwest, but analysis within states shows no relationship between the elasticity of housing supply and air pollution. Within states in Panel B, wildfires tend to occur in areas with inelastic housing supply, potentially both reflecting steep slopes and rugged terrain, but national data in Panel A show no relationship between wildfires and housing supply elasticities.

Figure 4 reports binned scatterplots of population growth versus each externality. In each graph, the vertical axis represents the log growth in county population between the 2000 and 2020 Population Censuses. The horizontal axis plots the mean value of each externality.

Patterns in Figure 4 differ across externalities. For air pollution, surface water pollution, and wildfires I detect no relationship between levels of the externality and population growth, and the slopes are flat. Other externalities have statistically significant relationships between population growth and levels of externalities, with varying signs. Spatial patterns of population growth are decreasing mean exposure to drinking water pollution and floods, as counties with the lowest exposures to these externalities had the most rapid population growth. The pattern for drinking water may arise because urban areas have rapid growth and low drinking water pollution. As discussed earlier, the spatial pattern for floods may reflect housing supply elasticities. Spatial patterns of population growth are increasing population mean exposure to heat, in line with continued growth in the Sun Belt.

Corresponding regressions in Table 5 show that people are moving away from drinking water pollution and floods, and towards extreme heat. I find no detectable relationship of population growth and environmental exposures for air pollution, surface water pollution, and wildfires. These point estimates are near zero, although the confidence intervals have moderate width. Panels A and B show that population and housing have similar patterns.

Sensitivity analyses in Appendix Table 7 using alternative datasets echo patterns of results from the main text, though provide some evidence that people are moving towards

locations with wildfires.

Appendix Table 8 looks only at the highest risk areas. The right tail of the risk distribution receives particular scrutiny. For example, the *New York Times* recently summarized, "More Americans Than Ever Are Living in Wildfire Areas" (Rojanasakul and Plumer 2025), using statistics on the top decile of the wildfire risk distribution. Appendix Table 8 finds similar patterns to the main text.

Overall, this analysis undermines the common assertion that people and housing are moving towards externalities. That conclusion could suggest that moral hazard is increasing environmental risks, or that population preferences are increasing risk of systemic disasters. People are moving towards extreme heat, but away from drinking water pollution and floods. Spatial moral hazard may be relevant for some externalities, but few patterns here are general.

6 Measuring Environmental Inequality

Many papers, discussed in the introduction, find that vulnerable populations experience higher levels of air pollution. Do these findings generalize to environmental quality overall?

Understanding environmental inequality matters for a few reasons. The distribution of environmental quality across income and demographic groups constitutes part of overall inequality. Accounting for environmental inequality therefore allows more complete analysis of redistribution and the Second Welfare Theorem. Additionally, environmental inequality influences the political economy of environmental policy.

Figure 5 plots the covariance between the level of an externality and the population share of a demographic group. Each underlying observation represents a county. Triangles describe poverty; solid circles describe the share Black; and squares describe the share Hispanic. For example, the top-left red square describes the covariance between the share of the population in each county that is Hispanic and the concentration in each county of $PM_{2.5}$. Horizontal bars plot 95% confidence intervals. Positive values indicate higher exposures to an externality; negative values indicate lower exposures. All demographics and externalities are measured in z-scores, to facilitate comparisons across externalities.

Figure 5 shows that poor communities have higher rates of each externality, making this a general pattern. The covariances vary, from 0.05 for wildfires to 0.35 for heat. All are positive

and statistically distinguishable from zero. This pattern may be general because disamenities like environmental externalities depress home values, and low-income households' lower expenditure on housing locates them in these lower-price areas.

Figure 5 finds less general patterns for Black and Hispanic communities. Both demographic groups have higher exposure to some externalities and lower exposure to others. Black communities face greater levels of air pollution, surface water pollution, floods, and heat. Black communities, however, face lower levels of drinking water pollution and wildfires. All these relationships reject the null hypothesis of zero correlation between demographics and externalities. The patterns for Black communities may reflect their geographic concentration in the South and in more densely populated counties. Hispanic communities face higher levels of surface water pollution, heat, and wildfires, but lower levels of air pollution. These patterns for Hispanic communities may reflect their concentration in the West and in rural areas. Notably, Black and Hispanic communities have opposite patterns for several demographics.

Table 6 reports corresponding regressions of demographics on externalities. These regressions do not seek to measure causal relationships, but instead to assess whether specific demographic groups experience higher or lower levels of some externalities. Odd-numbered columns use no additional controls. Even-numbered columns add state fixed effects, which estimate relationships within states. The first two columns analyze the poverty rate, the next two columns analyze the share Black, and the last two analyze the share Hispanic. This table measures externalities in physical units to facilitate interpretation in physical terms; I also report elasticities.

Table 6 echoes findings from the graphs. All coefficients in column (1) are positive and statistically significant, indicating that poor communities have greater exposure to all externalities. I find the largest elasticity of 0.12 for heat, partly because the South has high temperatures and low incomes. Most patterns persist with state fixed effects in column (2), although poor communities have lower air pollution within states, perhaps because more rural areas have cleaner air but more poverty. Patterns for Black communities in column (3) echo the graphs, and patterns persist within states—black communities have higher levels of some but not all externalities. The largest elasticity in the table is for Black communities' exposure to air pollution. This underscores the widely-documented pattern that Black households disproportionately experience high air pollution, and the

limited generality of this relationship for learning about other externalities and demographic groups. Patterns for Hispanic communities in column (5) also loosely echo the graphs.

Appendix Figure 4 presents sensitivity analyses, discussed in Appendix B.3, which echo some though not all of these specific patterns. The sensitivity analyses echo the broader finding that few patterns are general across externalities.

Overall, this section finds that some but not all patterns of environmental inequality are general. Poor communities face greater exposure to nearly all externalities. Black communities face greater air pollution levels, which is the strongest relationship I detect, and perhaps one reason why research has focused on this relationship. Hispanic communities do not face greater air pollution levels. These patterns for Hispanic and Black communities generalize to some but not all externalities. Sensible explanations, such as geographic concentrations of demographic groups and relationships between density and demographics, help explain why patterns do not readily generalize.

7 How Do Externalities Affect Spatial Economic Outcomes?

7.1 Model Details

This section uses a quantitative spatial equilibrium model to study how different environmental externalities affect population, real income, and social welfare across US counties. Many papers project spatial amenities on environmental and other observed variables (e.g., Roback 1982; Albouy 2016; Diamond 2016). This analysis instead uses independent information on the amenity value of environmental goods, then incorporates this information into the model to study its implications. I assume each externality affects amenities.[3] Because the model reflects standard spatial frameworks (Roback 1982; Allen and Arkolakis 2014; Arkolakis and Allen 2025), I describe assumptions informally here and formally in Appendix C.

Producers engage in perfect competition and produce output one-for-one from labor, hired at wage w_i. Labor productivity A_i differs by county. Due to iceberg trade costs, county i must ship $\tau_{ij} \geq 1$ units to county j for one to arrive.

[3]With information on effects of externalities on productivity, it would be straightforward to add that pathway also.

A continuum of individuals each supply one unit of labor. Individuals choose a county to live in and choose consumption of a variety that differs by location of origin in order to maximize utility. Labor is fully mobile, with no migration costs.

Individuals have constant elasticity of substitution utility across varieties produced in different locations. Total amenities u_j increase utility multiplicatively. These assumptions imply a county price index P_i and bilateral gravity expenditure that have standard constant elasticity form. They also imply that the welfare W_i of any person in county i equals total amenities u_i times real income w_i/P_i:

$$W_i = u_i \frac{w_i}{P_i} \tag{3}$$

Agglomeration forces operate through two channels. Total productivity A_i includes an exogenous component $\bar{A}_i$ and an endogenous component, via the elasticity α of productivity with respect to population. Total amenities u_i include an exogenous component $\bar{u}_i$ and an endogenous component, via the elasticity β of amenities with respect to population. I assume environmental quality directly affects exogenous amenities $\bar{u}$.

A spatial equilibrium is a distribution across counties of workers, wages, and price indices, given exogenous productivity, amenities, trade costs, and model parameters, satisfying four requirements: goods markets clear; budget constraints are satisfied; welfare equalizes across regions; and population summed across regions equals global population. I assume all counties have strictly positive population in baseline and counterfactual scenarios.

These assumptions imply the following system of nonlinear equations, which relates the exogenous amenity and productivity of each county to parameters, population and wage data, and trade costs:

$$L_i^{\tilde{\sigma}\gamma_1} = \bar{u}_i^{(1-\tilde{\sigma})(\sigma-1)} \bar{A}_i^{\tilde{\sigma}(\sigma-1)} W_i^{1-\sigma} \sum_S \tau_{s,i}^{1-\sigma} \bar{A}_s{}^{(1-\tilde{\sigma})(\sigma-1)} \bar{u}_s^{\tilde{\sigma}(\sigma-1)} \frac{\left(L_s^{\tilde{\sigma}\gamma_1}\right)^{\frac{\gamma_2}{\gamma_1}}}{\bar{L}} \tag{4}$$

Here S is the set of counties, $\bar{L}$ is national population, σ is the elasticity of substitution, $\gamma_1 \equiv 1-\alpha(\sigma-1)-\beta\sigma$ is the partial elasticity of local welfare with respect to local population, and $\tilde{\sigma} \equiv (\sigma-1)(2\sigma-1)$ and $\gamma_2 \equiv 1+\alpha\sigma+\beta(\sigma-1)$ are other parameter combinations.

Equilibrium also implies that a county's GDP $Y_i = w_i L_i$ is a function of exogenous productivity, exogenous amenities, and the price index. Solving for exogenous amenities

gives

$$\ln \bar{u}_i = \frac{\gamma_1}{(\sigma - 1)(1 + \alpha)} \ln Y_i + \nu_i \tag{5}$$

Here ν_i is a function of exogenous productivity, the price index, and model parameters. Equation (5) describes the marginal relationship between exogenous amenities $\ln \bar{u}_i$ and county GDP $\ln Y_i$. Intuitively, amenities provide a marginal contribution to GDP, a relationship I invert to obtain equation (5). I substitute the willingness to pay for a change in environmental quality, calculated from ex ante evidence (e.g., the pollution-mortality concentration-response function), into equation (5) to calculate the corresponding change in total amenities.

For example, let E_i denote the baseline cost of environmental externalities to county i in dollars. I calculate the increase in a county's exogenous amenities due to eliminating these environmental externalities as

$$\ln \bar{u}_i' = \ln \bar{u}_i + \frac{\gamma_1}{(\sigma - 1)(1 + \alpha)} \ln E_i \tag{6}$$

where u' denotes the value of u under a counterfactual (Dekle, Eaton and Kortum 2008).

Given a counterfactual change in environmental quality, I calculate equilibrium population L_i and welfare W_i for each county. For example, one counterfactual that I consider eliminates environmental externalities. I use equation (6) to calculate the implied counterfactual exogenous amenities, $\ln \bar{u}_i'$.

I parameterize the model as follows. I take county bilateral trade costs from Allen and Arkolakis (2014), who recover values consistent with the preceding model using transportation network data on rail lines, highways, and other infrastructure. I assume $\sigma = 9$, consistent with Eaton and Kortum (2002). I use wage and employment data from the Census. Finally, I assume benchmark spillovers of $\alpha = 0.1, \beta = -0.3$, given estimates of the elasticity of productivity with respect to population, the expenditure share on housing, and the assumption of perfect competition (Rosenthal and Strange (2004); Allen and Arkolakis (2014))

I primarily analyze a counterfactual that turns off environmental externalities, either for one externality at a time or all at once. Ongoing work analyzes a counterfactual that changes each externality to reflect climate change forecasts.

Spatial Equilibrium Results

For each county, Appendix Figure 6 maps the ratio of environmental externality costs to county GDP. Externality costs in Appendix Figure 6 have spatial patterns that loosely echo externalities in physical units from Figure 1. Both figures, for example, show that air pollution has greater severity in the Eastern US. Similarly, for floods, heat, and wildfires, regions of the country with high levels in Figure 1 generally have high costs in Appendix Figure 6.

Cross-county differences in the willingness to pay for environmental drive some differences between physical levels of externalities in Figure 1 and Appendix Figure 6. For example, air pollution particularly increases mortality for older Americans, so counties with older populations have greater estimated willingness to pay for air quality. Similarly, floods cause greater damage in areas with dense and high-value housing. Thus, air pollution, floods, heat, and wildfires have more spatial autocorrelation in Figure 1 than in Appendix Figure 6.

Panel A of Appendix Figure 6 shows the ratio of externality costs in dollars to county GDP.[4] Costs of externalities exceed 4% of GDP in parts of the Eastern industrial heartland, due substantially to air pollution. Externalities also exceed 4% of GDP in some Western countries, due to extreme cold and wildfires. In a typical county nationally, externalities have cost of 2 to 4 percent of GDP, though in some counties this share reaches 20 percent.

How does eliminating these externalities affect spatial patterns of real income, welfare, and population? Appendix Figure 7 solves equation (4) to calculate how counterfactual externalities affect real income. The changes have small magnitude impacts because they include only general equilibrium adjustments to wages and prices, and not the amenity value of the externalities (i.e., in equation 3, they reflect w_i/P_i but not u_i). Most changes in real income are below a fifth of a percentage point in absolute value, and median changes are a few hundredths of a percentage point. The spatial distribution of values make sense. For example, turning off heat disproportionately increases real incomes in the South, and turning off cold or wildfires particularly increases real incomes in the West.

Figure 6 maps the change in each county's population due to turning off externalities, calculated from solving equation (3) under a counterfactual. This map helps answer questions like "How many more people would live in Los Angeles if Los Angeles had no wildfire risk?"

Figure 6 shows that eliminating externalities dramatically changes population in many

[4]Figure 1 does not report a panel summing across externalities because physical units vary by externality.

counties. In areas of the Eastern US with severe air pollution and the Western US with severe cold and wildfires, eliminating externalities increases population by over 10 percent. Existing partial equilibrium analyses have studied how externalities affect home insurance values but not population (First Street Foundation 2025). This counterfactual causes modest population decreases in many counties with low baseline externalities. Of course, this counterfactual holds national population fixed.[5]

Figure 6 also shows intriguing spatial patterns of changes in population. Given much attention to coastal flooding (Balboni 2025; Desmet et al. 2021), one might expect the removal of externalities to affect coastal regions substantially. Instead, because air pollution and extreme temperatures have outsized welfare consequences for inland regions, the largest magnitude impacts occur inland. Population particularly increases in the Ohio River Valley around Kentucky, Indiana, Illinois, Ohio, and West Virginia where baseline air pollution is high, due partly to coal-fired electricity generation. Populations also expand in cold and fire-prone areas of the Western US.

Magnitudes of the population change in Figure 6 exceed magnitudes of the changes in real income and amenities for several reasons. Population responds to welfare, not just real income. Additionally, population may respond more than one-for-one to a given magnitude change in welfare, depending on the counterfactual equilibrium.

Table 7 provides statistics corresponding to these graphs. Panel A summarizes the willingness to pay for eliminating environmental externalities. Panel B describes how this change affects real income. Panel C summarizes the change in welfare, which equalizes across counties in this as in many spatial equilibrium models, and Panel D summarizes the change in population. Columns (1) through (5) describe the counterfactual change in one externality at a time, while column (6) describes the counterfactual change in all externalities at once.

Findings from Table 7 echo patterns in the maps. Air pollution accounts for just over half of marginal willingness to pay for the externalities, extreme temperatures for a fourth, and floods for most of the rest; wildfire costs are smaller on average, though more important for some regions. The change in welfare due to a counterfactual is orders of magnitude larger than the change in real income, again since welfare includes the direct amenity value while real income only accounts for general equilibrium adjustments. The unweighted mean change

[5]I abstract from the feedback loop that eliminating externality-induced mortality could increase total US population via longevity.

in population across counties due to eliminating all externalities is 8.3 percent, though of course a weighted mean across counties is zero since the maps assume that population is fixed under a counterfactual.

Like any model, this framework represents an abstraction and a few of its static assumptions are worth discussing. This analysis assumes that people perfectly perceive and rationally respond to environmental amenities. In reality, information about levels and health costs of air pollution is imperfect, though monitoring and awareness campaigns increase it (Greenstone et al. 2022; Barwick et al. 2024). This analysis also assumes away migration costs, which in reality can decrease population responses. I interpret model-based estimates as medium- to long-run comparative statics, holding other forces fixed. Finally, counterfactuals that completely eliminate wildfire risk, or flood risk, or extreme temperatures are not especially realistic in the foreseeable future. The goal of this analysis is not to assess impacts of a particular proposed policy, but instead to understand more broadly what total effect different externalities have on spatial economic outcomes.

8 Conclusions

Many papers study one externality and generalize conclusions; this paper studies many externalities but narrows conclusions. I consider air and water pollution, floods, extreme temperatures, and wildfires. Concern about "compound climate risks," focus on sources like coal-fired power plants, and text from many papers that generalize from analysis of one externality to discuss broad conclusions all suggest the prior that conclusions from one externality would readily generalize to others. This prior turns out to be wrong, and I find that cross-externality correlations average close to zero. Some correlations, like heat and surface water pollution, are large and positive. Others are negative. These correlations are small on average in part because geophysical and human drivers of externalities, like population density or rough terrain, have different-signed patterns across externality.

The paper's second part finds that economic conclusions from analyzing one externality do not readily extrapolate to others. I reaffirm that the Great Recession reduced air pollution, but find that it did not reduce other externalities. I echo the common finding that population and housing growth are concentrated in areas with extreme heat, but find that growth is decreasing population mean exposure to drinking water pollution and floods. While poor

communities do have higher exposure to all these externalities in the cross section, Black and Hispanic communities have greater exposure to some and less to others. Finally, a quantitative spatial equilibrium model provides disparate results about how addressing each externality affects patterns of real income, amenities, and welfare.

While this analysis provides broad evidence for the US, it leaves a few questions open for future work. First, while I pick four specific questions to revisit, other work could look at many other classic questions involving the environment and the economy. The growing use of administrative data has lead scholars to reassess answers to some classic questions in applied microeconomics; similarly, use of comparable data on many externalities may help revisit other environmental economics questions.

A final open question is how dynamic analysis could enrich or otherwise change this paper's findings, given that climate change is changing many of these externalities. The comparative static spatial model says little about the rates of population migration in response to gradual sea level rise, relative warming of some regions, or accelerating regional wildfire risks. Analyzing dynamics requires additional complexity, but facilitates analysis of questions like how migration frictions interact with changes to externalities.

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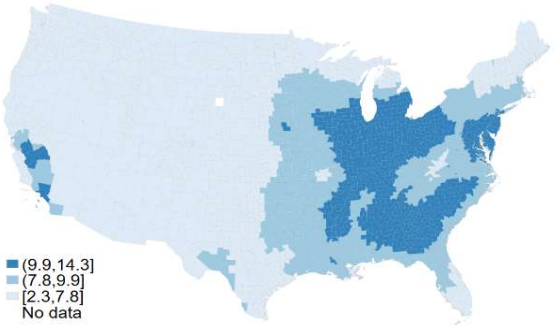
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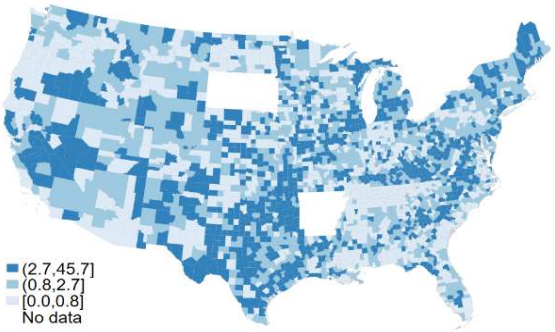
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Figure 1: Maps of Environmental Externalities

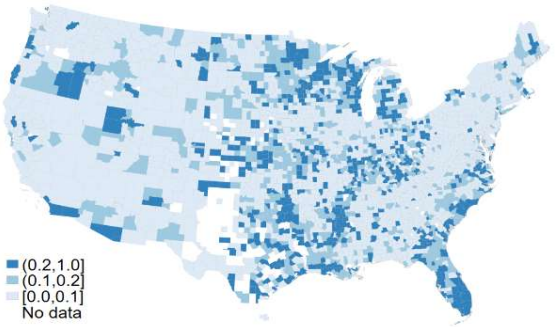
Panel A. Air pollution ($PM_{2.5}$ μg/m^3)



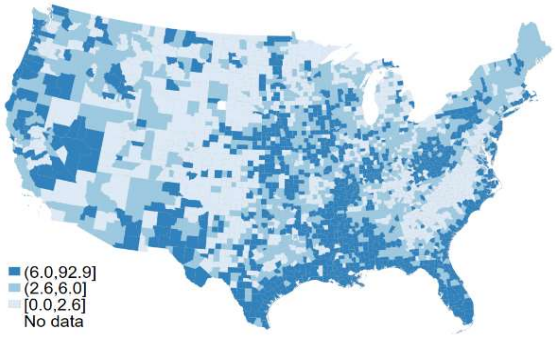
Panel B. Drinking water poll. (% violations)



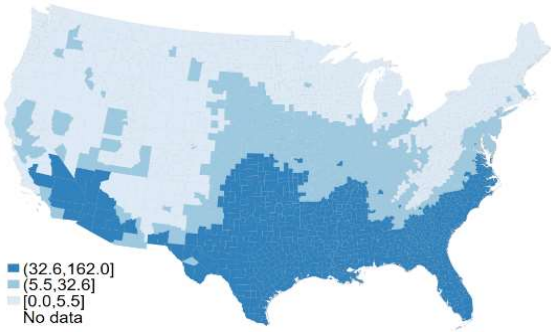
Panel C. Surface water poll. (% not fishable)



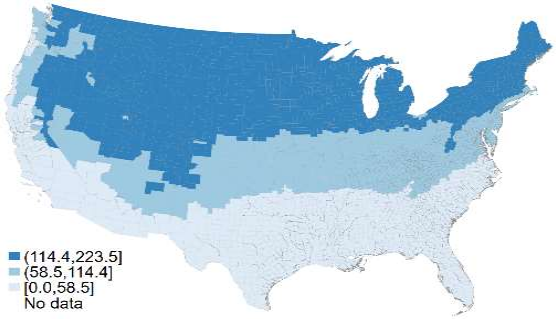
Panel D. Flood risk (% in floodplain)



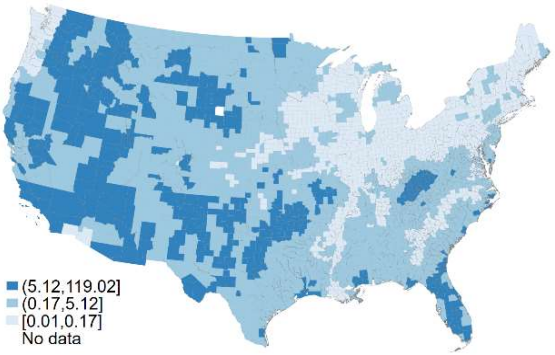
Panel E. Heat (days/year > 80°F)



Panel F. Cold (days/year < 40°F)



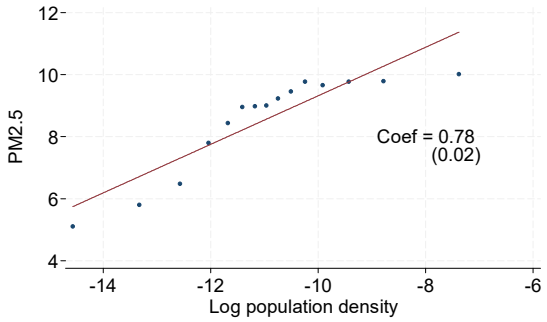
Panel F. Wildfire risk (expected damage)



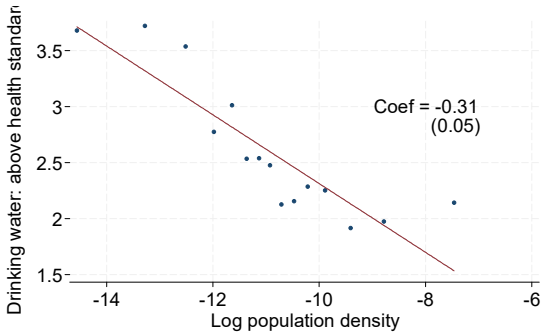
Notes: each map shows mean for each county. Data are averaged across years 2003-2019 or years available, listed in Appendix Table 1.

Figure 2: Population Density and Environmental Externalities

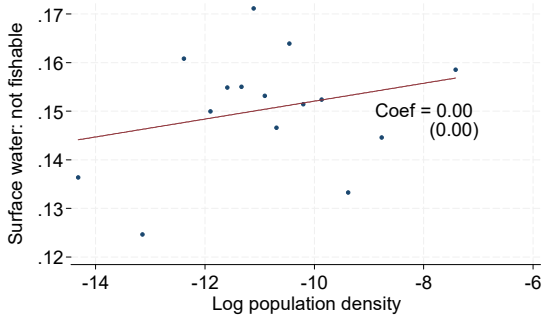
Panel A. Air pollution ($PM_{2.5}$ μg/m^3)



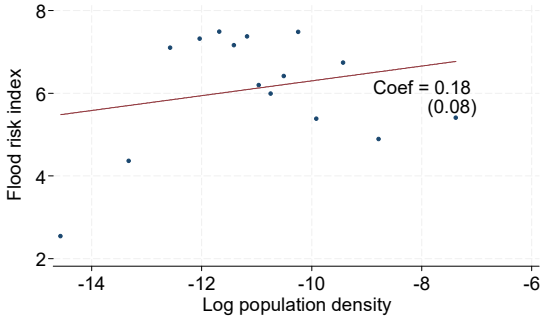
Panel B. Drinking water poll. (% violations)



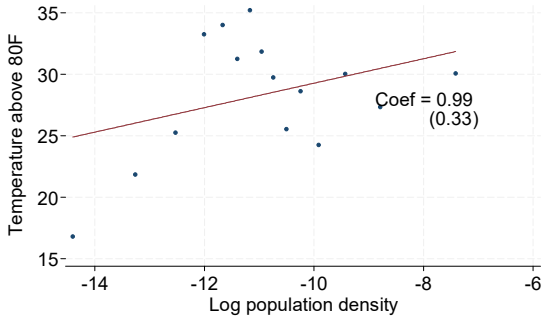
Panel C. Surface water poll. (% not fishable)



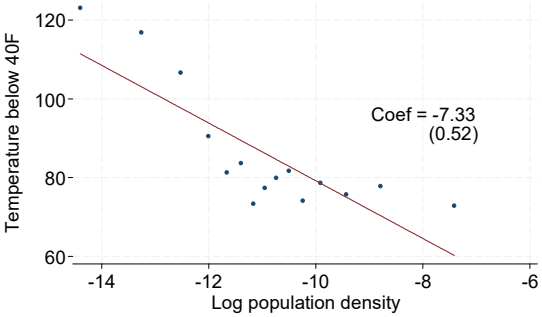
Panel D. Flood risk (% in floodplain)



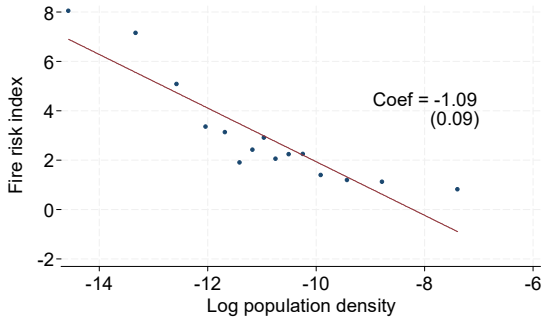
Panel E. Heat (days > 80°F)



Panel F. Cold (days < 40°F)



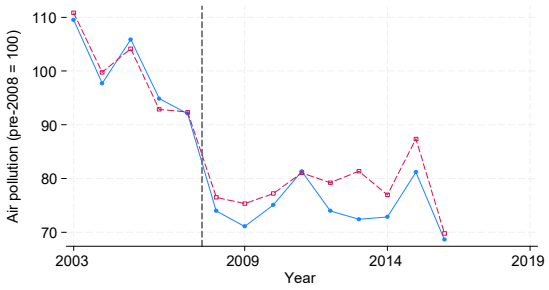
Panel G. Wildfire risk (expected damage)



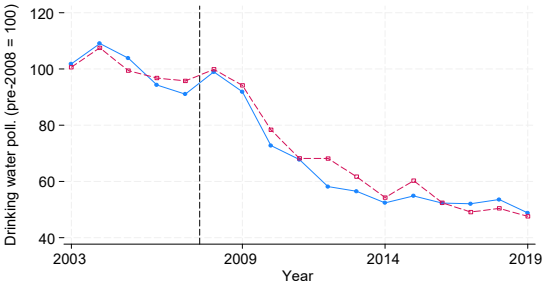
Note: Each graph shows binned scatterplot of one externality against log population per square mile. Each underlying observation represents a county. For each pollutant, data are averaged across years 2003-2019, or years shown in Appendix Table 1.

Figure 3: The Great Recession and Environmental Externalities

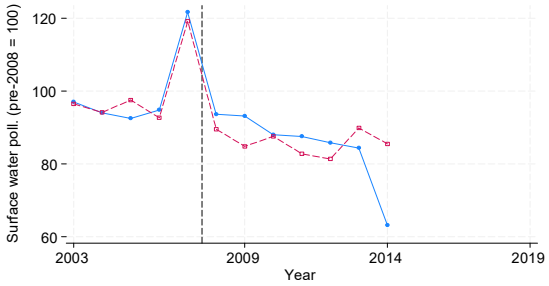
Panel A. Air pollution



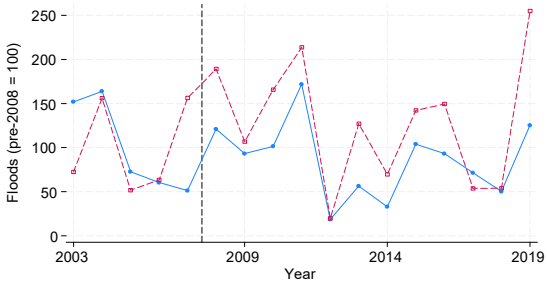
Panel B. Drinking water pollution



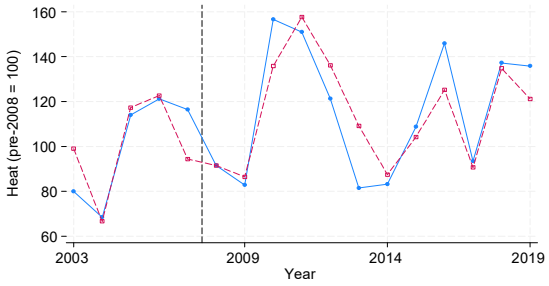
Panel C. Surface water pollution



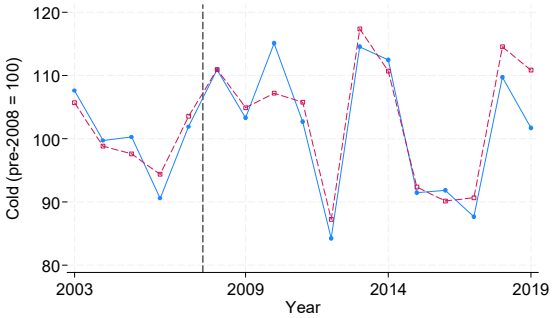
Panel D. Floods



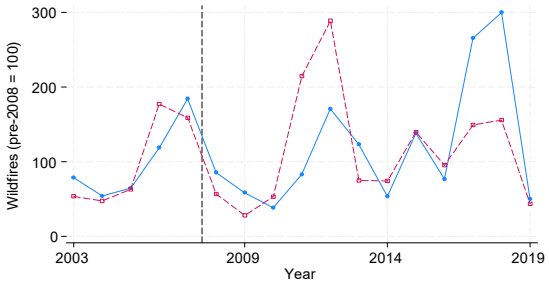
Panel E. Heat

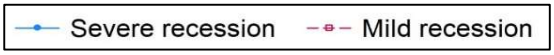


Panel F. Cold



Panel G. Wildfires

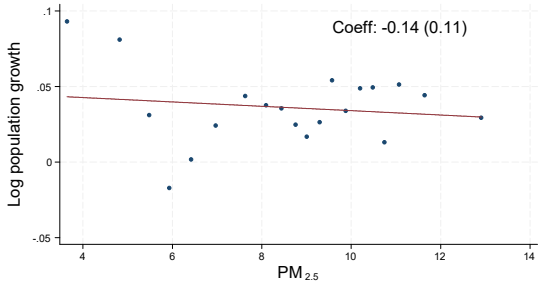




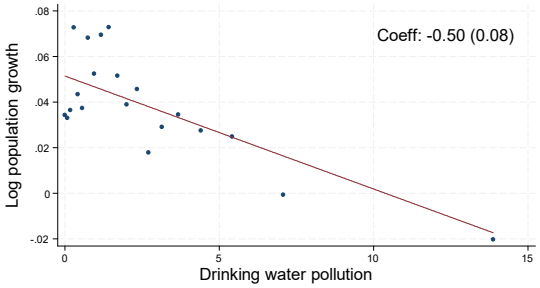
Notes: pre-2008 mean is normalized to 100.

Figure 4: Population Growth Versus Environmental Externalities Across Counties

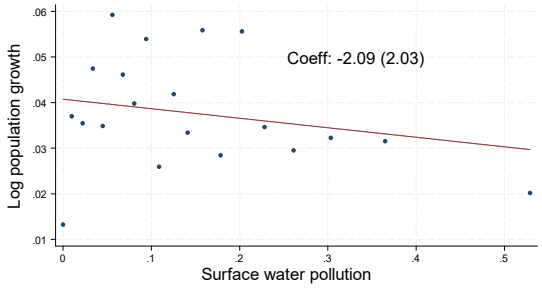
Panel A. Air pollution ($PM_{2.5}$ $\mu g/m^3$)



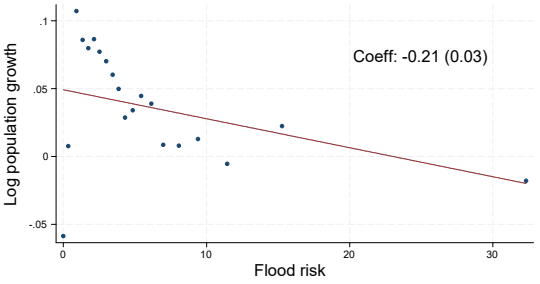
Panel B. Drinking water pollution (% viol.)



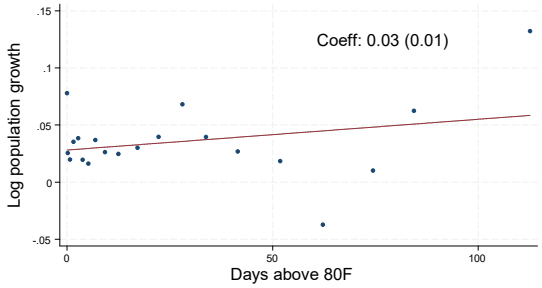
Panel C. Surface water pollution (% not fishable)



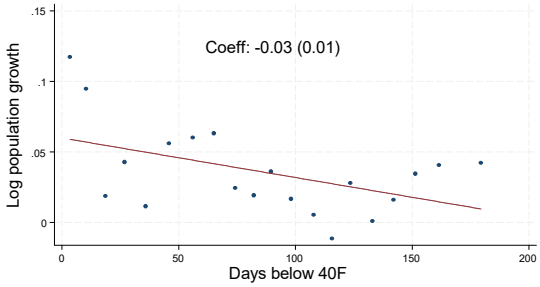
Panel D. Flood risk (% in floodplain)



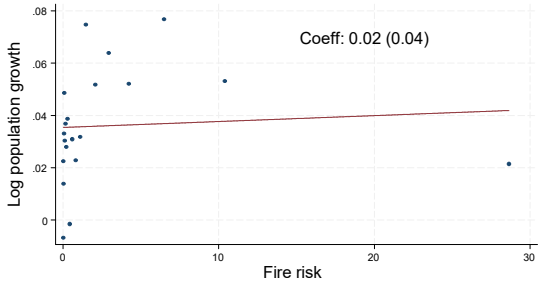
Panel E. Heat (days > 80°F)



Panel F. Cold (days < 40°F)

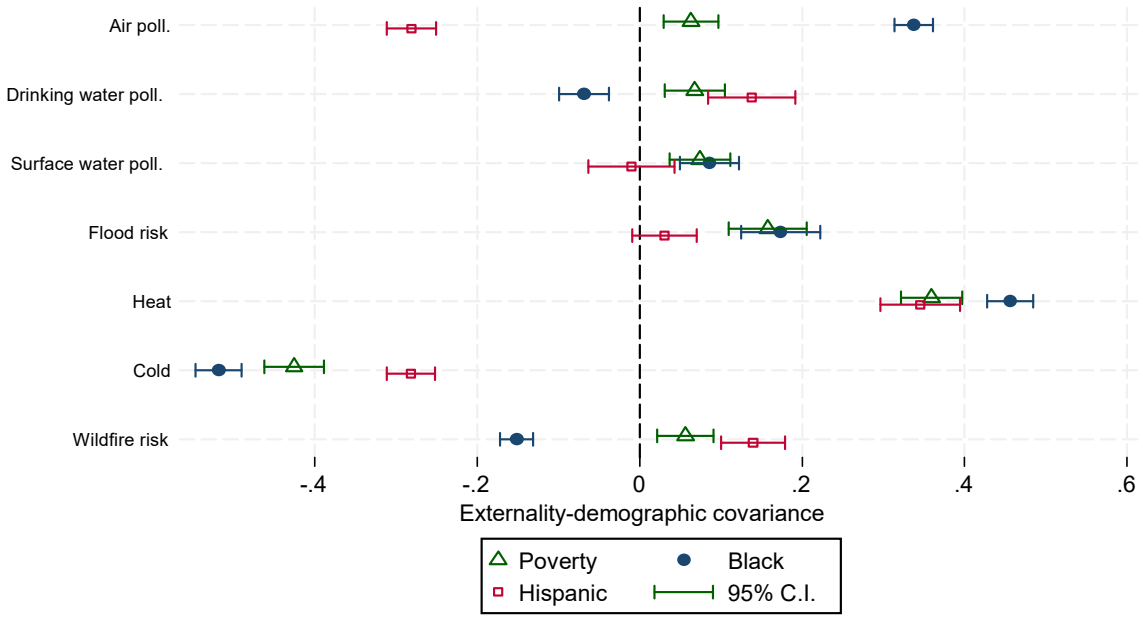


Panel G. Wildfire risk (expected damage)



Notes: Each graph shows a binned scatterplot. The vertical axis represents 2000-2020 log population growth in a county. The horizontal axis represents the mean value of the externality over the period 2003-2019 (or years for which data are available).

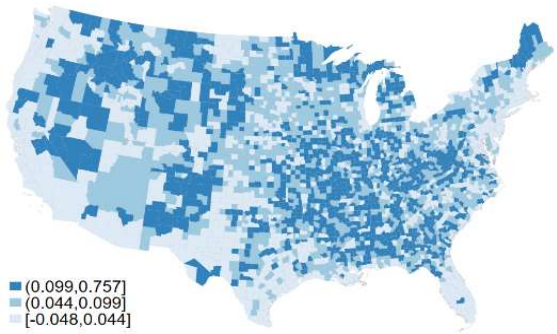
Figure 5: Inequality and Environmental Externalities



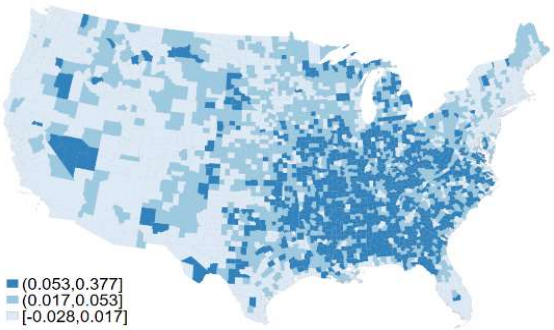
Note: graph shows point estimates from regressions of an externality on a demographic, both measured in z-scores, and a constant. Red horizontal lines show 95% confidence intervals from robust standard errors. Each observation in a regression represents one county. Poverty represents the share of households in poverty. Black and Hispanic represent the share of the county that identifies as this demographic.

Figure 6: Effects of Environmental Externalities on Population, Model-Based Estimates

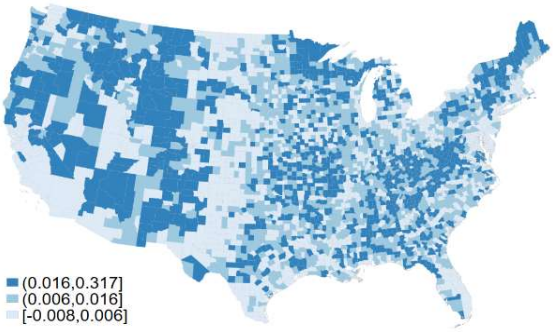
Panel A. All externalities



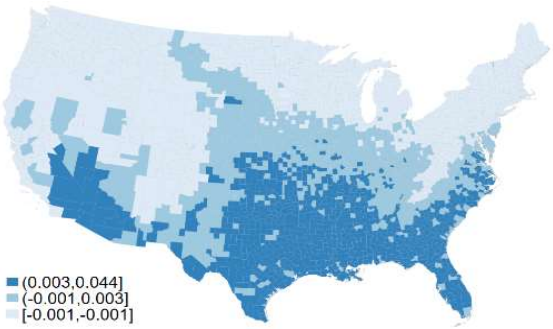
Panel B. Air pollution



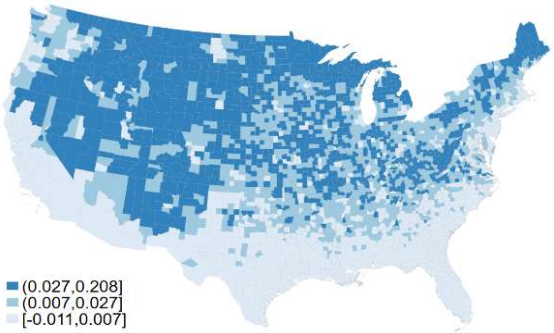
Panel C. Floods



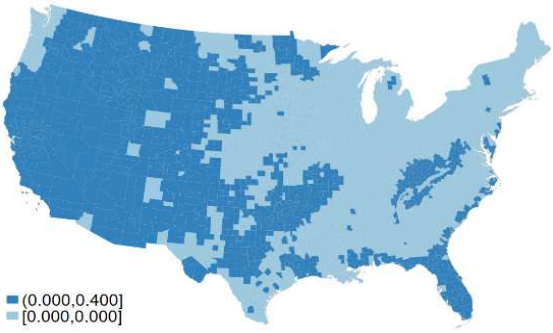
Panel D. Heat



Panel E. Cold



Panel F. Wildfires



Notes: Values represent share change in population, e.g., 0.10 represents a 10% increase in population

Table 1: Counties with Greatest Levels of Each Externality

(Units)		Air pollution ($PM_{2.5}$ $\mu g/m^3$)	Drinking water pollution (% Violations)	Surface water pollution (% Not fishable)	Floods (% In flood-plain)	Heat (Days/ year > 80°F)	Cold (Days/ year < 40°F)	Wildfires (Expected damage)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Extreme air pollution ($PM_{2.5}$ $\mu g/m^3$)								
Ottawa	OH	**14.27**	2.90	0.04	24.40	8.82	116.53	0.03
Erie	OH	**14.15**	1.43	0.11	8.70	7.88	114.29	0.02
Blackford	IN	**13.92**	0.09	0.11	2.30	7.94	113.18	0.02
Panel B. Extreme drinking water pollution (% violations)								
Loup	NE	5.82	**45.71**	0.09	4.40	7.12	130.06	0.99
Mason	TX	5.93	**44.35**	0.00	3.00	75.76	20.82	4.19
Mcculloch	TX	5.98	**44.32**	0.00	3.00	78.47	23.41	4.91
Panel C. Extreme surface water pollution (% not fishable)								
Tom Green	TX	7.30	1.63	**1.00**	4.90	76.41	25.47	5.02
Montague	TX	8.02	0.50	**1.00**	3.80	74.12	37.94	12.46
Lee	TX	7.28	0.44	**1.00**	3.20	106.53	12.24	1.09
Panel D. Extreme flood risk (% in floodplain)								
Cameron	LA	8.45	2.77	0.10	**92.90**	101.59	5.88	5.88
Monroe	FL	4.70	1.61	0.60	**91.90**	147.00	0.00	0.00
Hyde	NC	7.91	0.09	0.21	**88.50**	47.24	31.88	31.88
Panel E. Extreme heat (days/year > 80°F)								
Hidalgo	TX	6.65	0.98	0.00	5.80	**160.76**	1.82	0.70
Starr	TX	7.53	0.72	0.00	12.00	**160.53**	1.94	1.05
Zapata	TX	8.04	2.43	0.00	13.00	**156.94**	2.12	1.64
Panel F. Extreme cold (days/year < 40°F)								
San Juan	CO	3.59	0.33	0.04	2.60	—	**223.47**	3.34
Lake	CO	3.95	0.45	0.15	1.30	—	**223.29**	0.09
Hinsdale	CO	3.61	0.08	0.11	0.00	—	**214.76**	3.89
Panel G. Extreme wildfire risk (expected damage)								
Elko	NV	4.75	2.71	0.03	4.20	0.00	154.94	**119.01**
Boise	ID	4.71	2.11	0.03	2.70	0.35	165.76	**89.12**
Adams	ID	4.60	0.82	0.33	1.60	0.65	163.71	**76.13**

Notes: each panel shows counties with highest value of the variable listed in the panel title. The variable featured in each panel appears in bold.

Table 2: Correlations Between Environmental Externalities

	Air pollution (1)	Drinking water pollution (2)	Surface water pollution (3)	Floods (4)	Heat (5)	Cold (6)	Wildfire risk (7)
Panel A: Cross-sectional pairwise correlations							
Air pollution	1.00	—	—	—	—	—	—
	—	—	—	—	—	—	—
Drinking water poll.	-0.09	1.00	—	—	—	—	—
	[0.00]	—	—	—	—	—	—
Surface water poll.	0.05	0.01	1.00	—	—	—	—
	[0.01]	[0.50]	—	—	—	—	—
Flood risk	0.06	-0.01	0.12	1.00	—	—	—
	[0.00]	[0.69]	[0.00]	—	—	—	—
Heat	0.06	0.10	0.22	0.33	1.00	—	—
	[0.00]	[0.00]	[0.00]	[0.00]	—	—	—
Cold	-0.26	-0.06	-0.10	-0.27	-0.81	1.00	—
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	—	—
Wildfire risk	-0.31	0.11	-0.02	0.01	0.02	-0.03	1.00
	[0.00]	[0.00]	[0.32]	[0.57]	[0.22]	[0.14]	—
Mean correlation	-0.002						
Panel B: Panel pairwise correlations							
Air pollution	1.00	—	—	—	—	—	—
	—	—	—	—	—	—	—
Drinking water poll.	-0.02	1.00	—	—	—	—	—
	[0.00]	—	—	—	—	—	—
Surface water poll.	0.00	0.00	1.00	—	—	—	—
	[0.58]	[0.67]	—	—	—	—	—
Floods	0.04	0.01	0.02	1.00	—	—	—
	[0.00]	[0.02]	[0.01]	—	—	—	—
Heat	-0.03	0.00	-0.02	-0.05	1.00	—	—
	[0.00]	[0.77]	[0.01]	[0.00]	—	—	—
Cold	0.01	0.00	0.00	0.03	0.00	1.00	—
	[0.07]	[0.89]	[0.93]	[0.00]	[0.31]	—	—
Wildfires	0.04	0.00	0.00	0.01	0.01	0.00	1.00
	0.00	0.39	0.74	0.04	0.21	0.68	—
Mean correlation	0.003						

Notes: brackets show p-values. In Panel A, each observation is a county. In panel B, each observation is a county × year. Panel B shows pairwise correlations after partialling out year fixed effects and county fixed effects. Panel A units are as noted in Table 1. Panel B uses same variables and units, except floods (count) and wildfires (% acres burned) replace flood risk and wildfire risk since the former and not latter have panel data. "Mean correlation" excludes cold-heat correlation and own-externality correlations.

Table 3: Density and Spatial Patterns of Environmental Externalities

	Air pollution (1)	Drinking water pollution (2)	Surface water pollution (3)	Floods (4)	Heat (5)	Cold (6)	Wildfires (7)
Panel A. Population density, no fixed effects							
Log population density	0.782***	-0.307***	0.002	0.179**	0.994***	-7.325***	-1.086***
	(0.019)	(0.050)	(0.001)	(0.077)	(0.332)	(0.521)	(0.092)
R^2	0.333	0.023	0.001	0.002	0.003	0.06	0.069
N	3,134	2,975	2,926	3,134	3,103	3,103	3,133
Panel B. Population density, with state fixed effects							
Log population density	0.334***	-0.351***	0.004**	-0.257**	1.488***	-3.371***	-1.007***
	(0.014)	(0.058)	(0.002)	(0.106)	(0.218)	(0.303)	(0.107)
R^2	0.855	0.144	0.148	0.199	0.813	0.898	0.273
N	3,133	2,975	2,925	3,133	3,102	3,102	3,133
Panel B. GDP density, no fixed effects							
Log population density	0.653***	-0.300***	0.002	0.092	0.769**	-5.297***	-0.955***
	(0.021)	(0.043)	(0.001)	(0.078)	(0.317)	(0.498)	(0.081)
R^2	0.247	0.023	0.001	0.000	0.002	0.034	0.057
N	3,087	2,935	2,882	3,087	3,056	3,056	3,086
Panel D. GDP density, with state fixed effects							
Log population density	0.279***	-0.334***	0.004**	-0.257***	1.226***	-2.654***	-0.847***
	(0.013)	(0.047)	(0.002)	(0.094)	(0.178)	(0.261)	(0.086)
R^2	0.854	0.147	0.146	0.206	0.815	0.898	0.268
N	3,086	2,935	2,881	3,086	3,055	3,055	3,086

Notes: density equals population or GDP per square mile of land area. Population data is from 2010. Each observation represents a county. Units are as follows: air pollution ($PM_{2.5}$ ug/m^3); drinking water (% above standards); surface water (% not fishable); heat (days/year above 80°F); flood risk (index); wildfire risk (expected cost). Robust standard errors are in parentheses. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Table 4: The Great Recession and Environmental Externalities

(Units)	Air pollution ($PM_{2.5}$ $\mu g/m^{3)}$	Drinking water pollution (% Violations)	Surface water pollution (% Not fishable)	Floods (Count)	Heat (Days/ year > 80°F)	Cold (Days/ year < 40°F)	Wildfires (Count)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Great recession local shock × 1[year>=2007]	-0.084***	-0.044	0.000	-0.010	0.168	0.154	0.001
	(0.028)	(0.074)	(0.003)	(0.011)	(0.134)	(0.348)	(0.017)
County FE	X	X	X	X	X	X	X
DivisionXyear FE	X	X	X	X	X	X	X
N	34,496	32,079	18,100	34,529	34,133	34,133	34,474
Dependent var. mean	8.00	2.59	0.14	0.19	29.14	86.18	0.10

Notes: Great Recession shock represents the deviation of a county's 2007-2009 employment from trend. Standard errors clustered by county are in parentheses. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Table 5: Are People and Housing Moving Towards Externalities?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dependent variable: 100 × log 2003-2019 population growth								
Air pollution	-0.023	—	—	—	—	—	—	-0.109***
	(0.018)	—	—	—	—	—	—	(0.019)
Drinking water poll.	—	-0.118***	—	—	—	—	—	-0.138***
	—	(0.018)	—	—	—	—	—	(0.018)
Surface water poll.	—	—	-0.019	—	—	—	—	-0.011
	—	—	(0.018)	—	—	—	—	(0.019)
Floods	—	—	—	-0.113***	—	—	—	-0.175***
	—	—	—	(0.024)	—	—	—	(0.026)
Heat	—	—	—	—	0.058***		—	0.008
	—	—	—	—	(0.022)		—	(0.036)
Cold	—	—	—	—	—	-0.097***	—	-0.198***
	—	—	—	—	—	(0.020)	—	(0.030)
Wildfires	—	—	—	—	—	—	0.011	0.001
	—	—	—	—	—	—	(0.019)	(0.019)
N	3,134	2,975	2,926	3,134	3,103	3,103	3,133	2,771
Panel B. Dependent variable: 100 × log 2000-2020 housing unit growth								
Air pollution	0.027	—	—	—	—	—	—	-0.062***
	(0.018)	—	—	—	—	—	—	(0.020)
Drinking water poll.	—	-0.123***	—	—	—	—	—	-0.130***
	—	(0.018)	—	—	—	—	—	(0.020)
Surface water poll.	—	—	-0.008	—	—	—	—	-0.004
	—	—	(0.018)	—	—	—	—	(0.019)
Floods	—	—	—	-0.092***	—	—	—	-0.154***
	—	—	—	(0.024)	—	—	—	(0.026)
Heat	—	—	—	—	0.050**	—	—	0.016
	—	—	—	—	(0.022)	—	—	(0.038)
Cold	—	—	—	—	—	-0.094***	—	-0.167***
	—	—	—	—	—	(0.020)	—	(0.030)
Wildfires	—	—	—	—	—	—	-0.009	0.000
	—	—	—	—	—	—	(0.017)	(0.017)
N	3,133	2,972	2,926	3,133	3,102	3,102	3,132	2,771

Note: table shows beta coefficients. Each observation represents a county. Each column of each panel shows a separate regression. Parentheses show robust standard errors. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*). Units for each independent variable are shown in Appendix Table 1.

Table 6: Inequality and Environmental Externalities

	Poor (%)		Black (%)		Hispanic (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution ($PM_{2.5}$ μg/m^3)	0.17***	-0.44***	2.10***	2.26***	-1.57***	0.26
	(0.04)	(0.09)	(0.09)	(0.16)	(0.10)	(0.20)
Elasticity	0.08	-0.22	1.90	2.05	-1.62	0.26
N	3,133	3,132	3,134	3,133	3,134	3,133
Drinking water poll. (% viol.)	0.11***	0.14***	-0.28***	-0.04	0.54***	0.05
	(0.03)	(0.03)	(0.06)	(0.04)	(0.11)	(0.08)
Elasticity	0.02	0.02	-0.08	-0.01	0.17	0.02
N	2,975	2,975	2,975	2,975	2,975	2,975
Surface water poll. (% viol.)	3.39***	2.41***	9.78***	10.65***	-0.72	-0.54
	(0.87)	(0.79)	(2.17)	(1.64)	(1.88)	(1.45)
Elasticity	0.03	0.02	0.16	0.17	-0.01	-0.01
N	2,926	2,925	2,926	2,925	2,926	2,925
Flood risk	0.12***	0.06***	0.32***	0.06	0.05	0.05*
	(0.02)	(0.02)	(0.05)	(0.04)	(0.03)	(0.03)
Elasticity	0.04	0.02	0.21	0.04	0.04	0.04
N	3,133	3,132	3,134	3,133	3,134	3,133
Heat (days > 80°F)	0.07***	0.05***	0.21***	0.24***	0.14***	0.13***
	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Elasticity	0.12	0.08	0.63	0.71	0.49	0.43
N	3,103	3,102	3,103	3,102	3,103	3,102
Cold (days < 40°F)	-0.05***	-0.03***	-0.15***	-0.14***	-0.07***	-0.07***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Elasticity	-0.26	-0.17	-1.24	-0.76	0.01	0.00
N	3,103	3,102	3,102	3,103	3,132	3,132
Wildfire risk	0.05***	0.02	-0.31***	-0.16***	0.25***	-0.15***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)
Elasticity	0.01	0.00	-0.10	-0.05	0.09	-0.05
N	3,132	3,132	3,133	3,133	3,133	3,133
Panel Data		X		X		X
County FE		X		X		X
Year FE		X		X		X

Notes: each table entry shows a separate regression of the indicated demographic variable on the indicated externality. Each observation in columns (1), (3), and (5), is a county; each observation in columns (2), (4), and (6) is a county × year. Parentheses show robust standard errors. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Table 7: Effects of Eliminating Environmental Externalities on Outcomes: Model-Based Estimates

	Air Pollution	Flood	Heat	Cold	Wildfires	Total
	(1)	(2)	(3)	(4)	(5)	(6)
A. Improvement in amenities (% of baseline GDP)						
Mean	3.63	1.10	0.22	1.43	0.09	6.46
Std. dev.	(2.66)	(0.84)	(0.30)	(1.10)	(0.35)	(4.01)
Median	2.86	0.92	0.07	1.24	0.01	5.56
5th pctile	0.74	0.00	0.00	0.08	0.00	1.75
95th pctile	8.97	2.63	0.87	3.42	0.39	14.32
B. Change in real income (w/P)(% x 100))						
Mean	-1.94	-0.53	0.11	-1.51	-0.19	-3.61
Std. dev.	(10.07)	(4.45)	(1.04)	(4.96)	(2.27)	(18.05)
Median	-0.52	0.43	-0.04	-0.98	-0.03	-0.39
5th pctile	-21.11	-8.88	-1.19	-10.25	-1.20	-37.18
95th pctile	12.60	4.36	2.28	5.27	1.08	20.08
C. Change in welfare (u w / P)*(%)*						
Mean	0.71	0.22	0.03	0.24	0.01	1.21
Std. dev.	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D. Change in population (%)						
Mean	4.3	1.5	0.3	2.1	0.2	8.3
Std. dev.	(4.7)	(1.9)	(0.6)	(2.5)	(1.2)	(7.7)
Median	3.2	1.0	0.0	1.7	0.0	7.0
5th pctile	-1.1	-0.6	-0.1	-0.7	0.0	-1.2
95th pctile	13.6	4.8	1.5	6.8	0.8	22.9
E. Change in population (# of people)						
Mean	0.0	0.0	0.0	0.0	0.0	0.0
Std. dev.	(17,000)	(5,179)	(922)	(5,899)	(301)	(28,461)
Median	605	188	4	209	0	1,161
5th pctile	-1,104	-113	-181	-674	-72	-1,224
95th pctile	3,583	1,082	334	1,539	124	5,659

Notes: Panel A shows the ratio of willingness to pay for each externality to the counties baseline GDP,. as seen in Appendix Figure 6.

Online Appendix

How General Are Environmental Externalities?

Joseph S. Shapiro

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A Data

A.1 Air pollution

I measure ozone using a 1 km gridded daily layer covering the years 2000-2016, from Requia et al. (2020*b*). Each observation in this layer represents the daily maximum of 8-hour rolling averages of ozone; this 8-hour maximim is the daily ozone measure that the US National Ambient Air Quality Standards regulate. This layer represents predictions from a machine learning algorithm trained to predict ground-level ozone measurements from monitoring sites. The prediction variables include weather, remote sensing data, land use, output from chemical transport models. The algorithm uses an ensemble of a neural network, random forest, and gradient boosting algorithm. I use this layer rather than the raw monitoring data since monitors are sparse and cover only about a third of US counties.

I use a few steps to translate this layer to the county×year averages I analyze. First, I spatially join each gridded prediction point from Requia et al. (2020*b*) to the relevant county, covering the contiguous US. I calculate the arithmetic mean of 8-hour daily ozone across all prediction points within each county×day. Finally, for each county×year in 2000-2016 separately, I sum the number of days with mean ozone ≥ 70 ppb. For each county×year, I obtain one summary calculation representing the entire calendar year, and another covering only the summer ozone season (May 1 - September 30).

Ground level ozone is monitored by the Environmental Protection Agency, but their monitors are sparse and cover only about a third of counties. I therefore estimate surface level ozone (O_3) (Requia et al. 2020*b*). The estimates are created using a variety of variables such as the aforementioned ozone ground measurements from the EPA, meteorological variables, remote sensing data and more to generate daily 8 hour maximum ozone concentrations for the contiguous United States at the one square kilometer special level. Daily data exists from 2000-2016. I created a mapping between each square kilometer ozone reading and the counties of the contiguous US, linking each index of the raw ozone data array to a specific county. Once generated, all daily ozone files are read in and each ozone estimate can be quickly assigned to a county. From here, I take an arithmetic mean of all ozone ground estimates in each county, and the result is used to represent the 8 hour ground maximum for that county on that day. Finally, for each year 2000-2016, the number of days in each county with over 70 parts per billion O3 is calculated for both the whole year and just the summer months (May 1st - September 30th).

A.2 Temperatures

I acquire high resolution temperature for the contiguous United States from PRISM (2025). I use daily 4km×4km gridded mean temperature (F) estimates. I construct a mapping of between each grid and the counties of the contiguous US, and then mapped all daily estimates from 2003-2022 to their appropriate county. I then take an arithmetic mean of all mean temperature estimates in each county daily, and use this as the counties mean temperature for that day. he daily mean temperature averages the daily maximum and minimum. Finally, for each year 2003-2022 I calculate the number of days with mean over 80 degrees Fahrenheit in each county. Sensitivity analyses consider cooling degree days and heating degree days, relative to a reference of 65°F. Cooling degree days for county c in year y equal $CDD_{cy} = \sum_t (T_{cty} - 65)1[T_{cty} \geq 65]$, where T_{cty} is the mean temperature on day t. Heating degree days equal $HDD_{cy} = \sum_t (65 - T_{cty})1[T_{cty} \leq 65]$.

A.3 Drinking Water Pollution

I weight across systems within a county using each system's share of the county. I link each Census block to drinking water system that serves it using service territory maps (SimpleLab and EPIC 2022). Arkansas and South Dakota lack the drinking water data.

Sensitivity analyses study the number of federally-reported Safe Drinking Water Act violations per 100 persons in each county×year, which I calculate as follows. The Safe Drinking Water Information System (Envirofacts 2020), managed by the US Environmental Protection Agency, reports the total number of violations per drinking water system×year. I calculate the mean of this value across systems within a year, weighted by the number of people each system serves.

A.4 Surface Water Pollution

"Fishable" readings have biochemical oxygen demand below 2.4 mg/L, dissolved oxygen above 64 percent saturation, fecal coliforms below 1000 MPN/100mL, and total suspended solids below 50 mg/L, a definition William Vaughan originally developed for Resources for the Future (Keiser and Shapiro 2019).

A.5 Fires

The fire data come from a 30 meter raster layer. A sensitivity analysis measures the share of land area in each county that has burned in a wildfire (National Interagency Fire Center 2024).

A.6 GDP

County level GDP data is from the Bureau of Economic Analysis (2024). The BEA lacks GDP data for many counties in Virginia, instead offering data for combination areas– "areas consisting of one or two independent cities with 1980 populations of less than 100,000 combined with an adjacent county". For these combination areas, I divide out the total GDP of the area by the proportion of the population in each constituent part to create county level GDP estimates for Virginia.

A.7 Mortality

Mortality and population data come from 2015 CDC (2024) Wonder datasets. For each county x age group, we record the population and number of deaths in 2015. The CDC do not present or publish death counts of 9 or fewer, so if a county x age group in 2015 has less than 10 deaths, we use the total population and total deaths in that age group x county from 1999-2016 to compute a mortality rate. If this still has less than 10 deaths, we look at the mortality rate of the given age group in all other counties in the same commuting zone from Autor and Dorn (2013) and impute that. If there are still not 10 deaths, we impute the average mortality rate for this age group from the counties state.

A.8 Regional housing data

Housing data used in section six comes from the 2020 census. Starting this census, the Census began reporting at the level of Connecticut's county-equivalent planning region as opposed to at the county level. However, all environmental data I use reports at the county level in Connecticut. Thus, while I use 2020 census data for 49 states, for Connecticut I use 2020 census estimates to align with the environmental data.

A.9 Floods

Sensitivity analyses use the First Street Foundation's Flood Risk Score (Lewis 2024) and the mean number of floods per county×year.

A.10 Valuation

To estimate the effect of extreme heat and cold on mortality, I use estimates from Barreca et al. (2016), Table 3, Panel A, column (3).

Here R_c represents the observed monthly deaths per person in county c; $R_c^{'}$ represents the counterfactual value in a world without extreme weather; $D40$, $D80\text{-}90$, and 90 are days below 40F, 80-90F, or above 90F; and P_c is the baseline population. For example, given 3 million annual US deaths and average days in the three bins of (73.6, 25,7, and 1.1) from Barreca et al. (2016) Table 1, this implies that extreme temperature causes $3,000,000 \cdot (1 - exp\{0.0034 \cdot 73.6 + 0.0012 \cdot 25.7 + 0.0034 \cdot 1.1\})$=1 million excess deaths annually.

B Discussion of Additional Results

B.1 Maps of Externalities

Appendix Figure 1 maps the externalities I examine in sensitivity analyses. Many spatial patterns echo those from the main text, though not all. Panel A uses ground-based $PM_{2.5}$ monitors, in contrast with the remote sensing data used in the main analysis. Concentrations remain high in the east, in urban centers, and in California's Central Valley. Panel B reports an algorithmic estimate of ground-level ozone concentrations in each county. Ozone has somewhat opposite spatial patterns to $PM_{2.5}$, with the greatest concentrations in the west, reflecting ozone's dependence on heat and sunlight. I discuss ozone in the appendix only given $PM_{2.5}$'s much greater damages.

Appendix Figure 1, Panel C, reports the number of federally-reported drinking water violations for the average person in each year, using data from the Safe Drinking Water Information System. As in the main text, concentrations are geographically scattered, with high levels in some agricultural areas and some urban areas. Panel D shows one measure of surface water pollution from the microdata–dissolved oxygen deficits. This measure of pollution reaches high levels in the south, partly reflecting high temperatures, and assorted other parts of the country.

Appendix Table 1 also reports alternative measures of floods. Panel E shows the number of Presidential Disaster floods or severe flooding from storms declared in each county×year. Such floods are most common in the mid-west, Appalachia, New England, and parts of the Pacific Northwest, echoing some geographic patterns from the flood risk map in Figure 1 of the main text. Panel F shows the flood risk index from First Street, which has high levels in Appalachia, parts of the Midwest, as well coastal eastern and southern states.

The last three panels of Appendix Figure 1 also echo maps in Figure 1 of the main text. Panel G shows cooling degree days, a more flexible measure of extreme heat, which have similar spatial patterns to the number of days above 80°F from the main text. Panel H show that heating degree days, a measure of exposure to cold, have somewhat opposite patterns.

Panel I shows that wildfires occur in areas where Figure 1 indicates that wildfire risks are high.

B.2 Correlations Between Externalities

Appendix Table 3 shows correlations between alternative measures of each externality (in each row) and the measures of each externality that the main test reports (in each column). The numbers in bold show correlations within a given measure of pollution or externality (e.g., remote sensing versus ground-based measures of pollution). Panel A shows cross-sectional regressions, while Panel B shows correlations of values after residualizing county fixed effects and year fixed effects.

The bold entries in Panel A of Appendix Table 3 shows strong correlations within most measures of externalities. The high correlations help assuage the concern that the lower correlations in Table 2 reflect measurement error. For example, the remote sensing and ground-based measures of $PM_{2.5}$, shown in the top-right of the table, have a correlation of 0.68. Ozone and $PM_{2.5}$ have a negative correlation, given their distinct spatial signatures shown in Appendix Figure 1. The raw drinking water readings and federally-reported counts of violations have a correlation of 0.53. Although the number of floods has modest correlation with the main flood risk index, the First Street Flood index has a much stronger correlation. Overall, the bottom of Panel A indicates that the cross-sectional correlation within each externality is on average 0.57.

Panel A of Appendix Table 3 also shows small and often negative correlations between externalities. The correlations are shown between the main variables and sensitivity analyses. For example, floods have a positive spatial correlation of 0.12 with air pollution but a negative corelation of -0.18 with heat. The bottom of Panel A shows that across different pollutants and externalities, the mean correlation is barely different from zero, at -0.01.

Panel B of Appendix Table 3 also shows strong correlations within externalities and weak correlations across externalities. The bottom of the panel shows that the mean correlation within an externality is 0.45, somewhat smaller than the value reported in Panel A. The mean correlation across externalities is also near zero, at 0.02.

B.3 Environmental Inequality

Appendix Figure 4 shows that some though not all of patterns on inequality from the main text persist in sensitivity analyses. For example, in these sensitivity analyses, poor communities have greater levels of most but not all externalities—they experience fewer surface water pollution violations and fewer heating degree days. Hispanic communities have lower

levels of $PM_{2.5}$ but higher levels of ozone, partly because ozone concentrations are greater in the West. Appendix Table 9, which repeats this analysis using alternative measures of environmental externalities, suggests broadly similar patterns.

C Quantitative Spatial Equilibrium Model

This model expands on the main text, and builds on canonical quantitative spatial equilibrium models (Roback 1982; Allen and Arkolakis 2014; Arkolakis and Allen 2025).

Production

Goods are produced one-for-one from labor at the price w_i under perfect competition. The price of varieties produced in county i and sold in county j is then

$$p_{ij} = \tau_{ij} \frac{w_i}{A_i} \tag{C–1}$$

Iceberg trade costs imply that $\tau_{ij} \geq 1$ units must be shipped for one to arrive. Each worker in county i has productivity A_i.

Consumption

An agent $l \in \mathcal{L}$ chooses which county $i \in \mathcal{N}$ to live in and chooses consumption of each variety of final good c_{ij} to maximize utility subject to a budget constraint:

$$\max_{\{c_{ij}\} \geq 0} \left(\sum_{i \in \mathcal{N}} c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} u_j \quad \text{s.t.} \sum_{i \in \mathcal{N}} p_{ij} c_{ij} \leq w_j \tag{C–2}$$

The agent derives constant elasticity of substitution utility from consuming varieties differentiated by country of origin, c_{ij}, with elasticity $\sigma \geq 0$. Amenities u_j multiplicatively increase utility. The worker purchases variety c_{ij} at price p_{ij}, and sells one unit of labor inelastically at the wage w_j.

Utility maximization (C–2) implies that the welfare of an agent in county i equals the product of real income and amenities:

$$W_i = \frac{w_i}{P_i} u_i$$

The price index $P_j = \left(\sum_i p_{ij}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ reflects CES utility. CES utility also implies that total expenditure by agents in county j on varieties produced in county i equals the GDP of

county j, $w_j L_j$, times the share of county j's expenditure going to county i:

$$X_{ij} = \left(\frac{p_{ij}}{P_j}\right)^{1-\sigma} w_j L_j \tag{C–3}$$

Substituting pricing (C–1) into (C–3) implies the "gravity" equation that the value of bilateral trade moves proportionally to GDP and inversely proportional to trade costs:

$$X_{ij} = \left(\frac{w_i \tau_{ij}}{A_i P_i}\right)^{1-\sigma} w_i L_i$$

Agglomeration

Agglomeration forces can affect amenities and productivity. Amenities include an exogenous component $\bar{u}_i$, which depends in part on environmental externalities. Amenities also include an endogenous component which responds to local population L_i, with elasticity β:

$$u_i = \bar{u}_i L_i^{\beta}$$

Local productivity A_i also includes an exogenous component A_i and an endogenous component, which responds to local population with elasticity α:

$$A_i = \bar{A}_i L_i^{\alpha}$$

Equilibrium

An equilibrium is a distribution of workers across counties $\{L_i\}$, wages $\{w_i$, and price indices $\{P_i\}$ satisfying four requirements. Goods market clearing requires that labor income equals sales:

$$w_i L_i = \sum_j X_{ij}$$

Regional budget constraints require that total expenditure in each location equals total income:

$$w_i L_i = \sum_j X_{ji}$$

Welfare in each region equals the constant W, with equality for $L_i > 0$:

$$W_i \leq W$$

Finally, the total population of each county equals national population $\bar{L}$:

$$\sum_i L_i = L$$

Under the assumption of symmetric trade costs $\tau_{ij} = \tau_{ji} \quad \forall i, j \in \mathcal{N}$, combining these results provides the system of equations described in the main text, which I solve to describe a counterfactual equilibrium.

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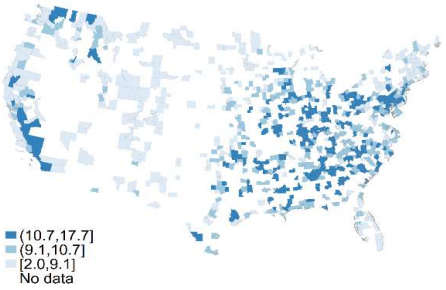
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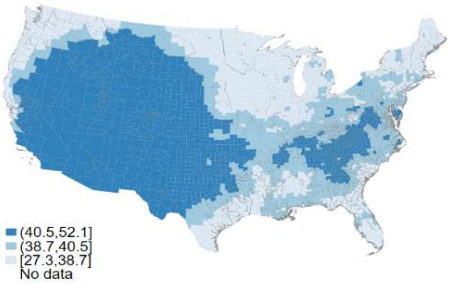
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Appendix Figure 1: Maps of Environmental Externalities, Sensitivity Analysis

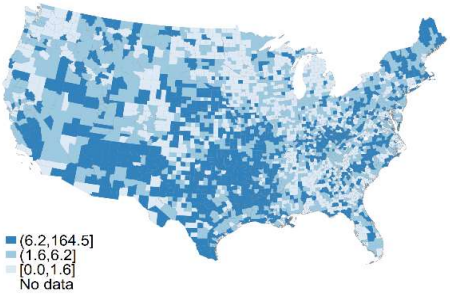
Panel A. Air pollution monitors ($PM_{2.5}$ $\mu g/m^3$)



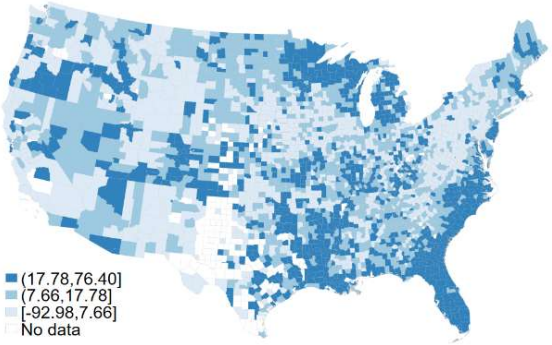
Panel B. Air pollution (O_3 ppb)



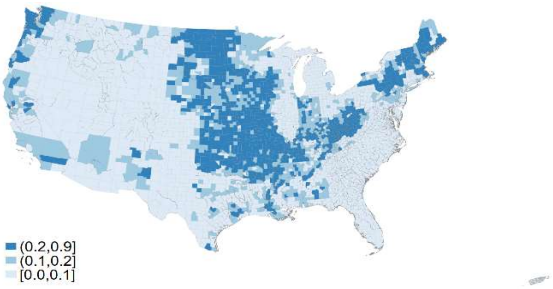
Panel C. Drinking water federally-reported viol's (annual #/100 people)



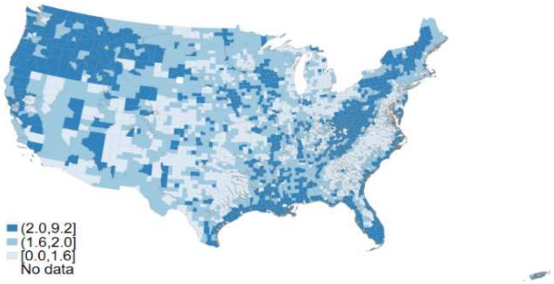
Panel D. Surface water dissolved oxygen deficits (%)



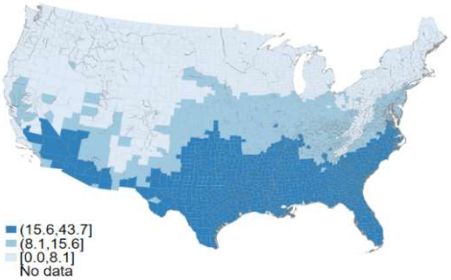
Panel E. Floods in mean year



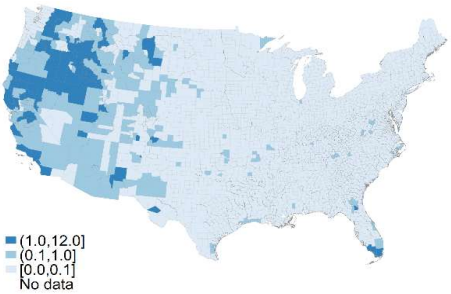
Panel F. Flood Risk (First Street index)



Panel G. Cooling degree days ('00s)



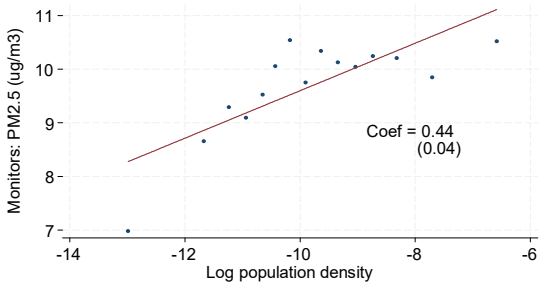
Panel I. Wildfires (% area burned in mean year)



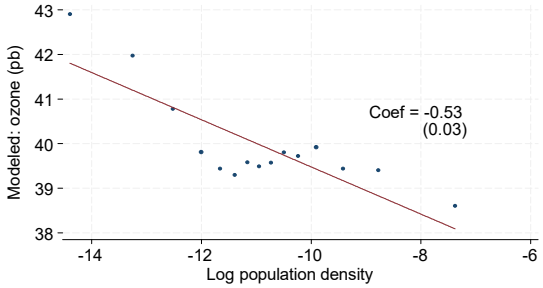
Notes: each figure shows the mean level of the indicated externality in a county across all available years in 2003-2019; Appendix Table 1 shows years available for each dataset. Viol's are violations.

Appendix Figure 2: Density and Environmental Externalities, Sensitivity Analysis

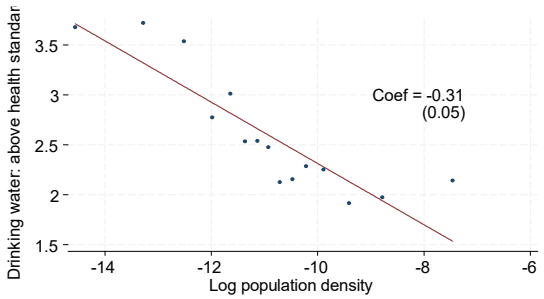
Panel A. Air pollution monitors ($PM_{2.5}$ μg/m^3)



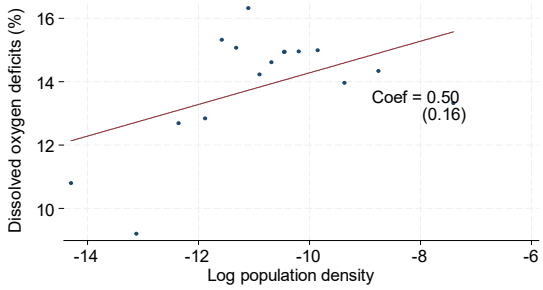
Panel B. Air poll. remote sensing (O_3 ppb)



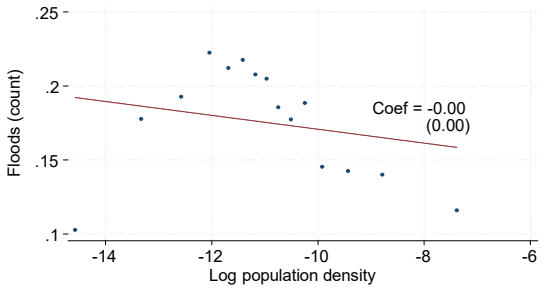
Panel C. Drinking water federally-reported violations (annual # / 100 people)



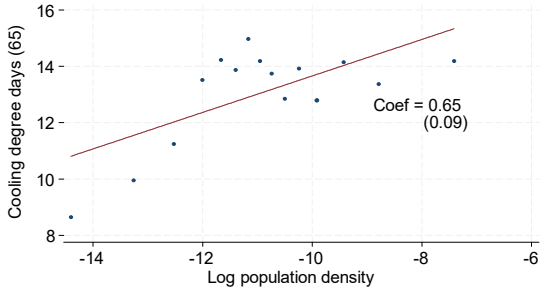
Panel D. Surface water oxygen deficits (%)



Panel E. Floods in mean year



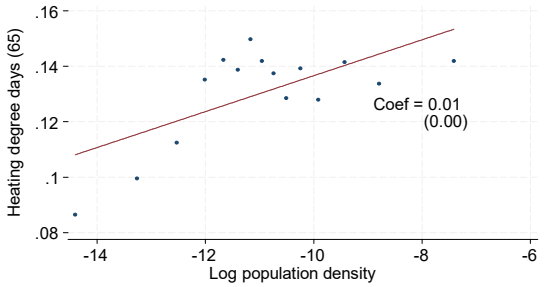
Panel F. Cooling degree days



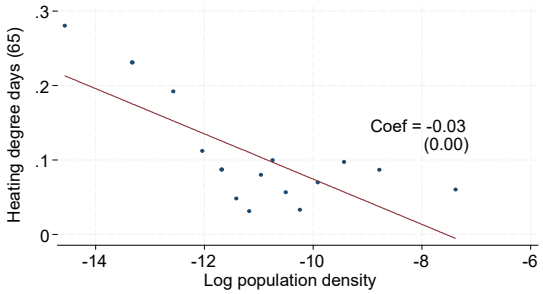
(Continued next page)

Appendix Figure 2: Density and Environmental Externalities, Sensitivity Analysis (continued)

Panel G. Heating degree days

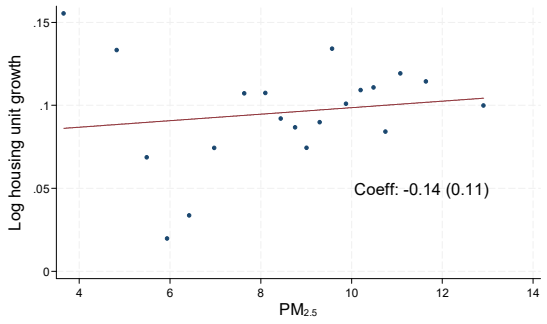


Panel H. Wildfires (% burned in mean year)

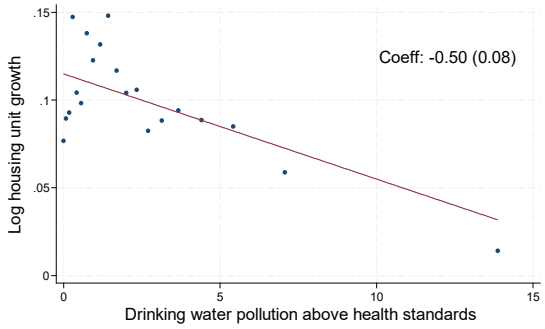


Appendix Figure 3: Housing Unit Growth Versus Environmental Externalities

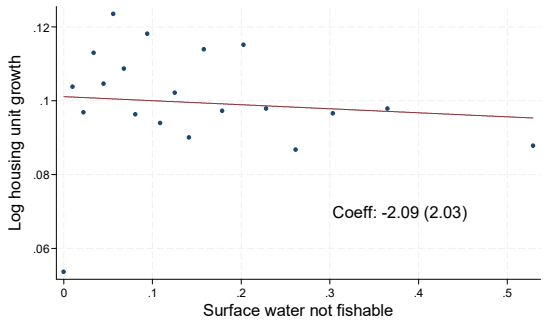
Panel A. Air pollution ($PM_{2.5}$ μg/m^3)



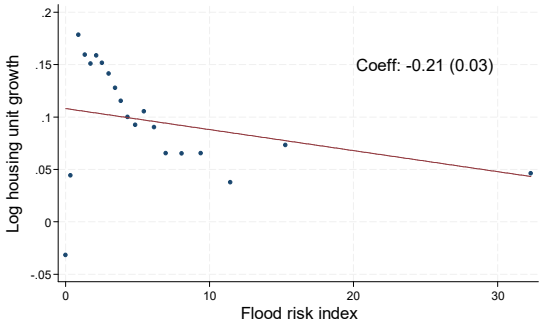
Panel B. Drinking water poll. (% violations)



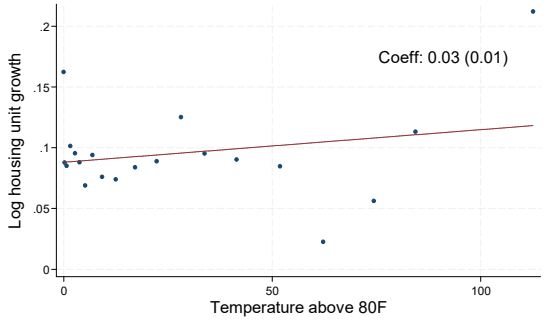
Panel C. Surface water poll. (% not fishable)



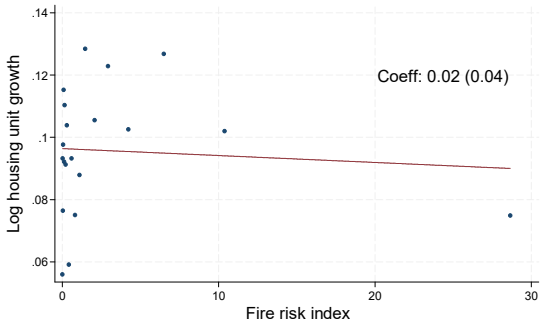
Panel D. Floods (% in floodplain)



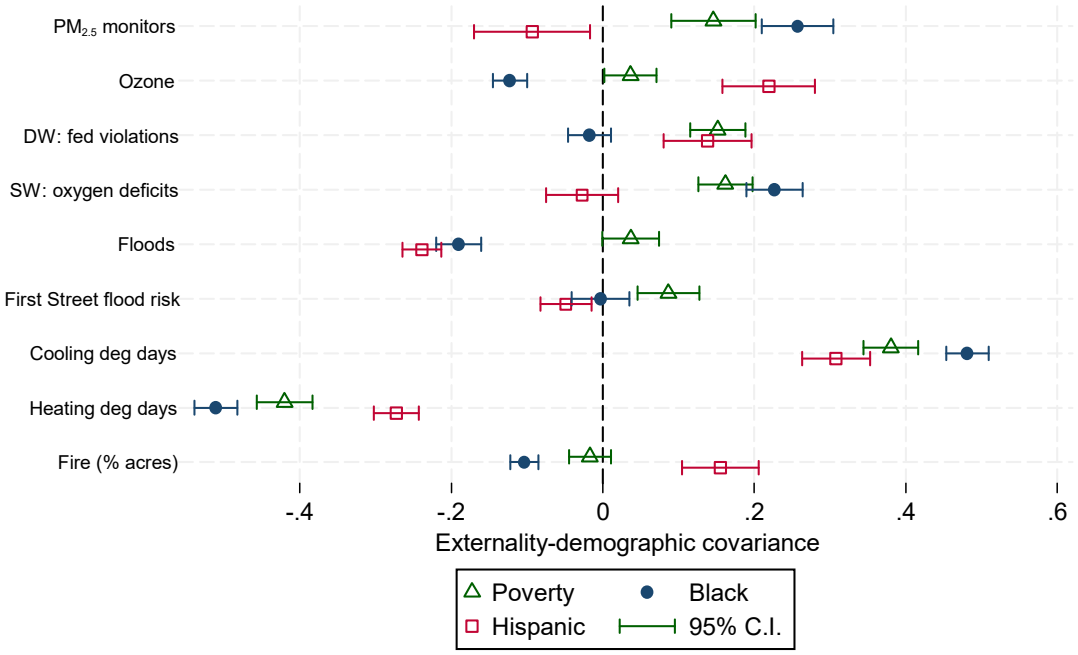
Panel E. Heat (days/year > 80°F)



Panel F. Wildfires (expected damage)

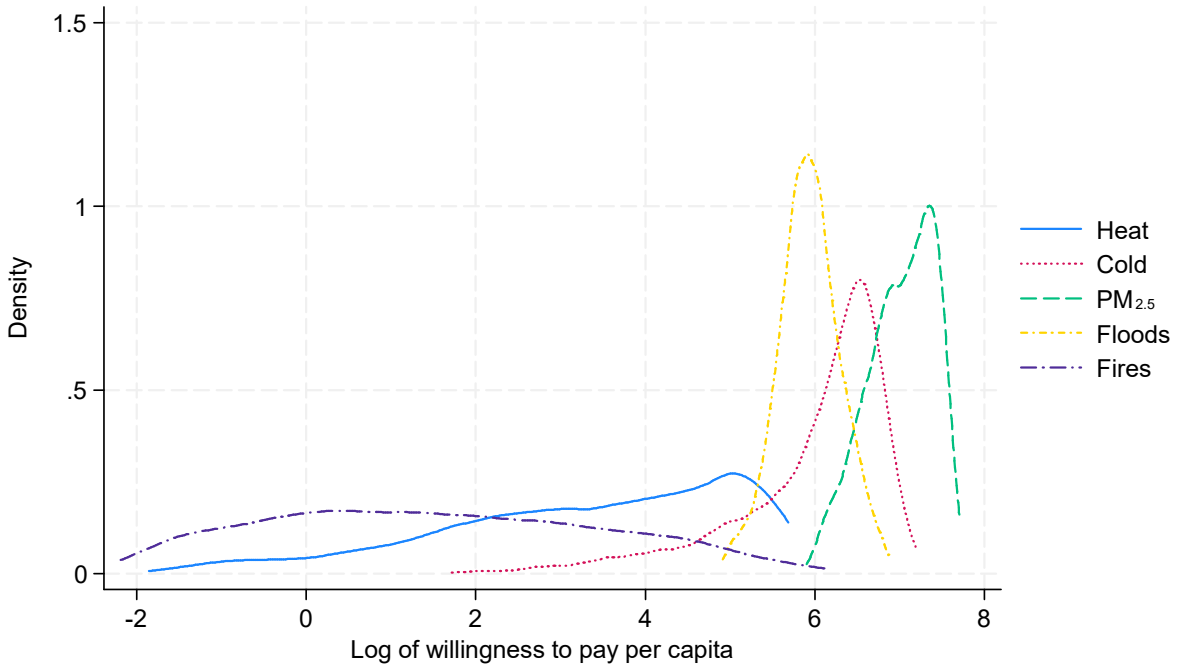


Appendix Figure 4: Inequality and Environmental Externalities, Sensitivity Analysis



Note: graph shows point estimates from regressions of an externality on a demographic, both measured in z-scores, and a constant. Red horizontal lines show 95% confidence intervals from robust standard errors. Each observation in a regression represents one county. Poverty represents the share of households in poverty. Black and Hispanic represent the share of the county that identifies as this demographic in the 2010 census.

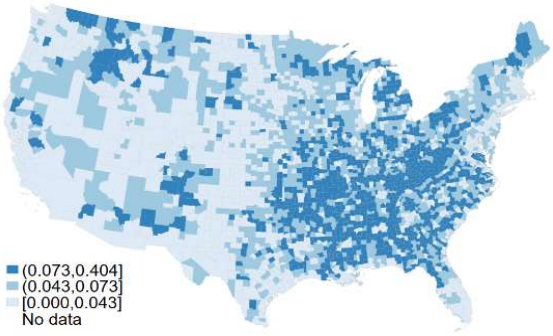
Appendix Figure 5: Distribution of Willingness to Pay for Environmental Externalities



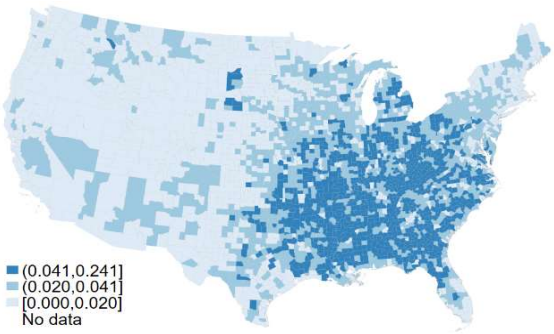
Notes: graph excludes top and bottom 1% of each externality. Each curve shows the distribution across counties.

Appendix Figure 6: Ratio of Annual Externality Costs to County GDP

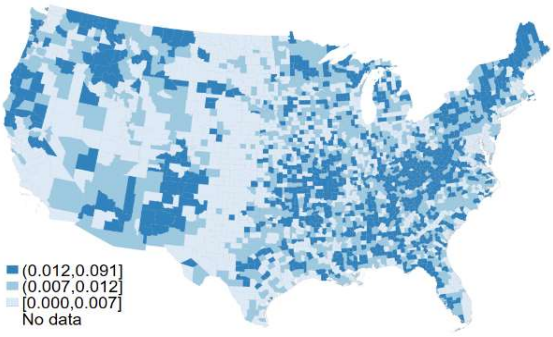
Panel A. All Externalities



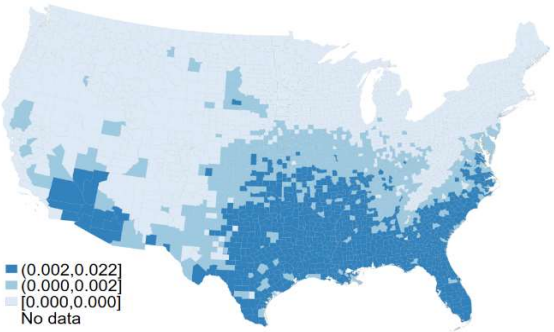
Panel B. Air pollution



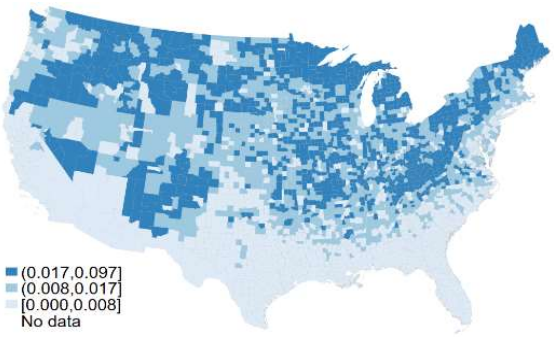
Panel C. Floods



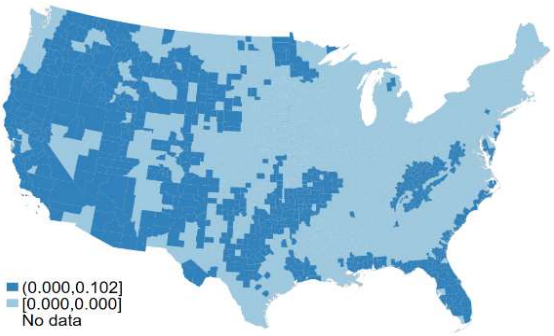
Panel D. Heat



Panel E. Cold



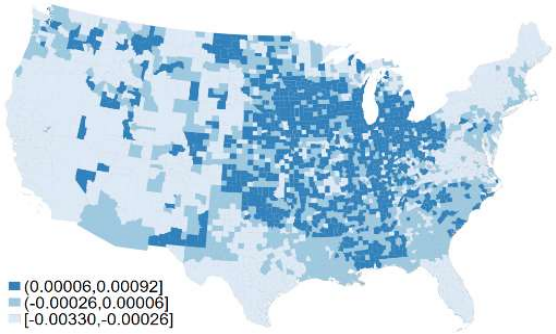
Panel F: Wildfires



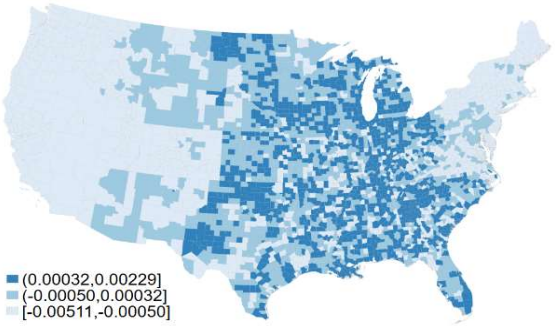
Notes: each map shows the ratio of the willingness to pay for each environmental externality to GDP for each county.

Appendix Figure 7: Effect of Turning Off Environmental Externalities on Real Income

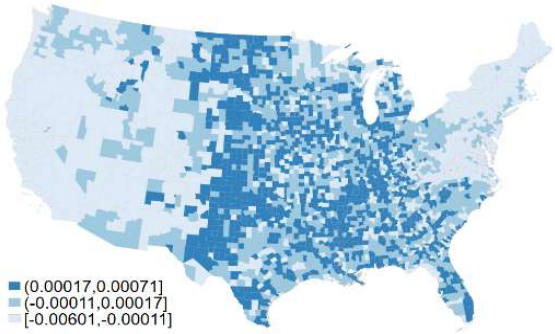
Panel A. All Externalities



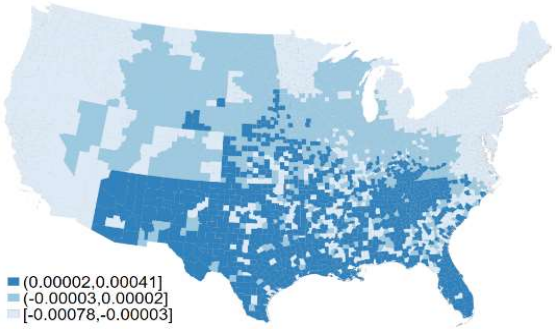
Panel B. Air pollution



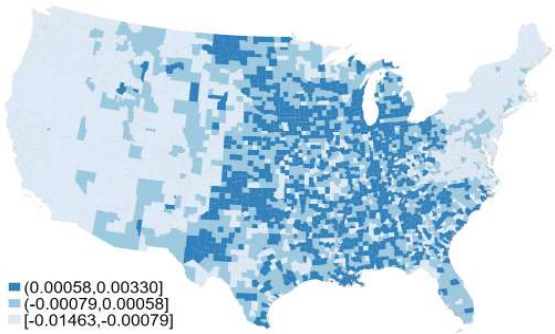
Panel C. Floods



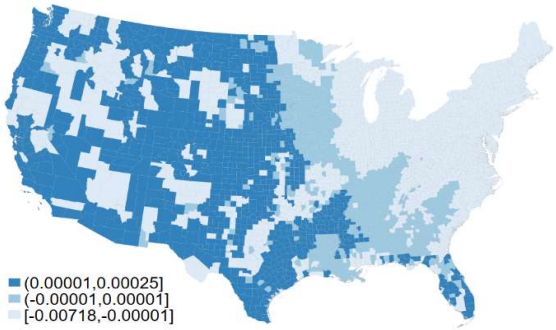
Panel D. Heat



Panel E. Cold

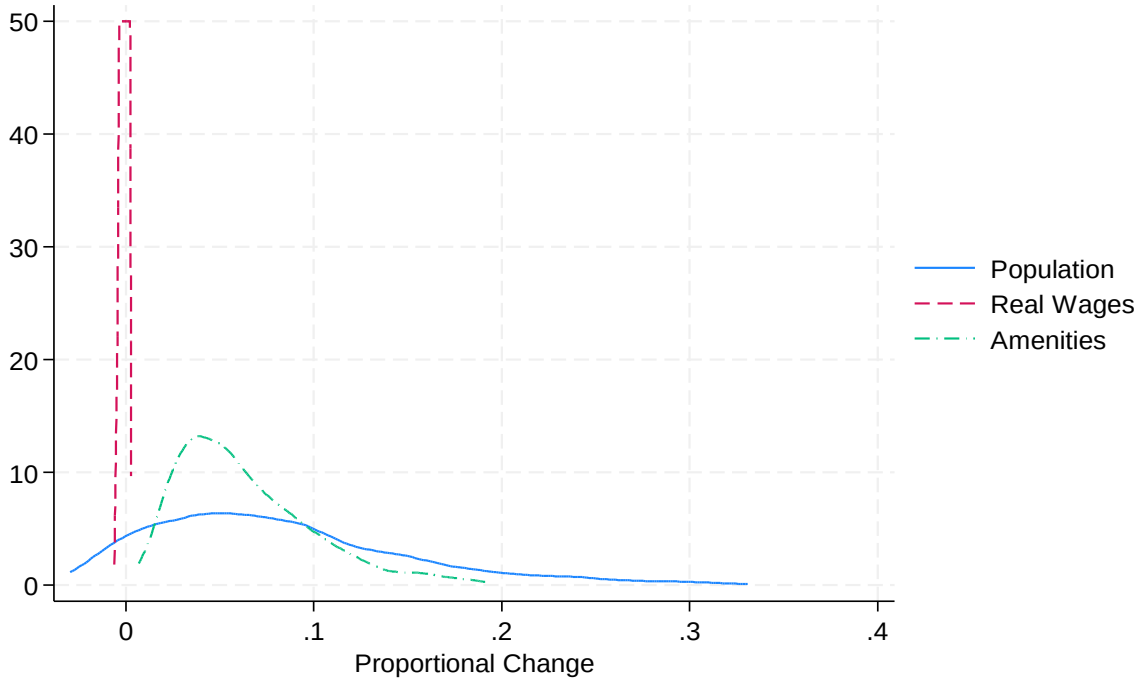


Panel F. Wildfires



Notes: real income in the model is wi/Pi. Each map shows mean for each county and externality across all available years in 2003-2019, listed in Appendix Table 1.

Appendix Figure 8: Effects of Turning Off Environmental Externalities on Spatial Outcomes



Notes: graph shows proportional density of proportional change ((new value - old value) / old value) across counties for four outcomes of interest. graph excludes top and bottom 1% of each externality. Each curve shows the distribution across counties. Wage density is capped at 50 for ease of viewing.

Appendix Table 1: Summary Statistics

	Units (1)	Mean (2)	Std. Dev. (3)	Median (4)	5th pctile (5)	95th pctile (6)	N (7)	Years (8)	Source
Panel A. Cross section									
Air pollution ($PM_{2.5}$ RS)	$\mu g/m^3$	8.36	(2.62)	8.82	4.02	12.11	3,220	1998-2016	NASA (2018)
Air pollution ($PM_{2.5}$ monitors)	$\mu g/m^3$	9.49	(2.16)	9.81	5.52	12.44	1,236	2000-2024	EPA (2024)
Air pollution (ozone RS)	ppb	39.98	(2.86)	39.65	36.30	45.80	3,109	2003-2016	Requia et al (2021)
Drinking water poll.	%>stds	2.61	(3.55)	1.57	0.00	8.62	2,982	2003-2019	Keiser et al. (2023)
Drinking water (viol's / 100ppl)	#	7.86	(13.54)	3.70	0.00	29.41	3,131	2003-2019	SDWIS (EPA 2024)
Surface water poll.	%>stds	0.15	(0.13)	0.12	0.00	0.42	2,928	2003-2014	Keiser & Shapiro (2019)
Surface water (oxygen deficits)	%	13.84	(13.74)	12.02	-5.10	38.68	2,908	2003-2019	Keiser & Shapiro (2019)
Floods (100-yr floodplain)	%	6.13	(7.92)	4.00	0.00	19.25	3,220	2024	First Street (2024)
Floods (First Street risk)	Index	1.98	(0.81)	1.80	1.35	3.26	3,220	2024	First Street (2024)
Floods	Count	0.16	(0.15)	0.13	0.00	0.43	3,246	2003-2019	FEMA (2024)
Heat (days)	#>80°F	28.50	(32.17)	14.45	0.05	92.00	3,105	2003-2022	PRISM (2024)
Cooling degree days (65°F '00s)	Index	13.04	(8.25)	11.59	2.19	27.39	3,105	2003-2022	PRISM (2024)
Heating degree days (65°F '00s)	Index	49.68	(22.19)	48.51	16.23	87.77	3,105	2003-2022	PRISM (2024)
Wildfire risk	E[damage]	3.01	(7.28)	0.52	0.02	14.34	3,141	2020	Scott et al (2020)
Wildfires	% acres	0.10	(0.46)	0.00	0.00	0.58	3,221	2003-2019	NIFC (2024)
Panel B. Panel, after partialling out county fixed effects and year fixed effects									
Air pollution ($PM_{2.5}$ RS)	$\mu g/m^3$	0.00	(0.95)	-0.03	-1.43	1.52	45,080	—	NASA (2018)
Air pollution ($PM_{2.5}$ monitors)	$\mu g/m^3$	0.00	(1.25)	-0.06	-1.82	1.86	15,956	—	EPA (2024)
Air pollution (ozone RS)	ppb	0.00	(1.29)	0.00	-2.16	2.13	43,526	—	Requia et al (2021)
Drinking water poll.	%>stds	0.00	(4.68)	-0.42	-4.80	6.36	49,271	—	Keiser et al. (2023)
Drinking water (viol's / 100ppl)	#	0.00	(17.03)	-1.83	-17.10	27.23	53,187	—	SDWIS (EPA 2024)
Surface water poll.	%>stds	0.00	(0.12)	-0.01	-0.17	0.20	24,769	—	Keiser & Shapiro (2019)
Surface water (oxygen deficits)	%	0.00	(11.67)	-0.05	-16.55	17.42	24,109	—	Keiser & Shapiro (2019)
Floods	Count	0.00	(0.43)	-0.10	-0.46	0.82	58,139	—	FEMA (2024)
Heat	#>80°F	0.00	(8.45)	-0.03	-12.88	13.93	62,100	—	PRISM (2024)
Cooling degree days (65°F '00s)	Index	0.00	(1.26)	-0.06	-1.90	2.05	62,100	—	PRISM (2024)
Heating degree days (65°F '00s)	Index	0.00	(2.46)	-0.04	-4.00	4.09	62,100	—	PRISM (2024)
Wildfires	% acres	0.00	(1.09)	0.01	-0.31	0.06	54,587	—	NIFC (2024)

Notes: RS is remote sensing, viol's are violations. Cross-sectional datasets have a single year in column (8) of Panel A and do not appear in Panel B.

Appendix Table 2: Annual Cost Estimates for Natural Disasters

	Per capita ($)	National total (bn$)
	(1)	(2)
Avalanche	0.24	0.08
Coastal flooding	3.82	1.28
Cold wave	2.81	0.94
Drought	4.98	1.67
Earthquake	61.97	20.74
Hail	6.34	2.12
Heat wave	67.04	22.44
Hurricane	6.9	2.31
Ice storm	2.28	0.76
Landslide	0.71	0.24
Lightning	2.42	0.81
Riverine flooding	20.17	6.75
Strong wind	6.68	2.24
Tornado	30.21	10.11
Tsunami	0.01	0.00
Volcanic activity	0.74	0.25
Wildfire	10.4	3.48
Winter weather	1.46	0.49
Total	229.2	76.72

Note: data from the National Risk Index, compiled by the Federal Emergency Management Agency.

Appendix Table 3: Correlations Between Externalities, Sensitivity Analysis

	Air pollution (1)	Drinking water pollution (2)	Surface water pollution (3)	Floods (4)	Heat (5)	Wildfires (6)
Panel A. Cross section						
Air poll. ($PM_{2.5}$ monitors)	**0.68**	0.03	-0.01	0.02	0.16	-0.11
Air poll. (Ozone RS)	-0.31	0.05	-0.11	-0.14	-0.07	0.28
Drinking water poll. (violations / 100ppl)	-0.12	**0.53**	0.08	0.04	0.21	0.16
Surface water poll. (% oxygen deficits)	0.06	-0.02	**0.72**	0.16	0.31	-0.01
Floods	0.12	0.03	0.02	**0.07**	-0.18	0.00
Floods: First Street flood index	-0.06	-0.05	-0.02	**0.65**	0.09	0.11
Cooling degree days (65°F '00s)	0.22	0.10	0.20	0.32	**0.97**	-0.01
Heating degree days (65°F '00s)	-0.31	-0.06	-0.11	-0.29	-0.82	-0.02
Wildfires (% acres)	-0.23	-0.04	-0.05	0.03	-0.09	**0.39**
Mean across externalities	0.01					
Mean within externality	0.57					
Panel B. Correlation after partialling out county fixed effects and year fixed effects						
Air poll. ($PM_{2.5}$ monitors)	**0.42**	-0.01	0.01	0.04	0.09	0.09
Air poll. (Ozone RS)	0.16	-0.02	-0.02	-0.12	0.35	0.01
Drinking water poll. (violations / 100ppl)	0.01	**0.09**	0.00	0.03	0.00	0.00
Surface water poll. (oxygen deficits)	-0.01	0.00	**0.60**	0.01	-0.03	0.00
Floods	0.04	0.01	0.02	—	-0.05	0.01
Cooling degree days (65°F '00s)	-0.09	0.00	-0.01	-0.09	**0.70**	0.01
Heating degree days (65°F '00s)	0.16	0.00	0.00	0.12	-0.06	-0.01
Wildfires (% acres)	0.04	0.00	0.00	0.01	0.01	—
Mean across externalities	0.02					
Mean within externality	0.45					

Notes: Values in bold represent comparisons within a pollutant or category of externality. "Mean across externalities" shows the mean value of all non-bold table entries. Rows show externalities measured in sensitivity analyses; columns show externalities measured in main text.

Appendix Table 4: Regressions of One Externality on Others

	Air pollution	Drinking water pollution	Surface water pollution	Extreme heat	Wildfire risk	Flood risk
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution	—	0.002	0.409	0.107***	-0.006	2.723**
	—	(0.475)	(0.312)	(0.013)	(0.010)	(1.288)
Drinking water poll.	0.000	—	-0.026**	0.002***	0.002***	-0.081*
	(0.001)	—	(0.012)	(0.001)	(0.000)	(0.049)
Surface water poll.	0.002	-0.056*	—	0.003***	-0.009***	-0.010
	(0.001)	(0.029)	—	(0.001)	(0.001)	(0.065)
Extreme heat	0.306***	3.612***	2.156***	—	0.023*	30.104***
	(0.038)	(1.003)	(0.497)	—	(0.014)	(2.795)
Wildfire risk	-0.025	4.044***	-10.239***	0.032	—	4.671
	(0.039)	(1.109)	(1.049)	(0.022)	—	(3.607)
Flood risk	0.001**	-0.016	-0.001	0.004***	0.000	—
	(0.000)	(0.010)	(0.006)	(0.000)	(0.000)	—
N	2,744	2,744	2,744	2,744	2,744	2,744

Note: table shows beta coefficients from a regression of the externality indicated in a column on all variables described in a given panel. Data represent a cross-section of US counties. Robust standard errors in parentheses. Appendix Table 1 lists units.

Appendix Table 5: The Great Recession and Environmental Externalities, Sensitivity Analysis

	(1)
Air pollution:	0.014
$PM_{2.5}$ monitors	(0.042)
N	9,390
Air pollution:	-0.058
ozone model	(0.066)
N	34,177
Drinking water:	-0.28
federal violations	(0.182)
N	34,327
Surface water:	-0.051
oxygen deficits	(0.279)
N	17,667
Floods	-0.01
	(0.011)
N	34,529
Cooling degree	6.247**
days	(2.801)
N	34,133
Heating degree	-16.474**
days	(6.980)
N	34,133
Wildfires	0.001
	(0.017)
N	34,474

Notes: Table shows regressions of indicated variable on shock. Standard errors clustered by county are in parentheses. Units are listed in Appendix Table 1. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 6: Externalities and Housing Supply Elasticities

	Air pollution (1)	Drinking water pollution (2)	Surface water pollution (3)	Extreme heat (4)	Wildfire risk (5)	Flood risk (6)
Panel A: No additional controls						
Housing supply elasticity	0.300***	0.007	0.001	-0.785***	1.126	-0.229***
	(0.065)	(0.058)	(0.004)	(0.279)	(0.977)	(0.078)
N	775	749	754	775	773	774
R^2	0.03	0.00	0.00	0.02	0.00	0.01
Panel B: Add state fixed effects						
Housing supply elasticity	-0.009	0.056	-0.003	-0.877***	-1.093**	-0.142**
	(0.038)	(0.076)	(0.004)	(0.318)	(0.521)	(0.072)
N	773	748	752	773	771	773
R^2	0.81	0.22	0.23	0.38	0.85	0.42

Appendix Table 7: Are People and Housing Moving Towards Externalities? Sensitivity Analysis

Dependent var	Log pop. (1)	Log pop. (2)	Log housing units (3)	Log housing units (4)
Air poll.: $PM_{2.5}$ monitors	-0.411*	-0.674***	-0.498**	-0.695***
	(0.218)	(0.228)	(0.251)	(0.262)
N				
Air poll.: ozone model	0.260***	0.173	0.179	0.280*
	(0.096)	(0.139)	(0.116)	(0.166)
Drinking water: federal violations	-0.129***	-0.178***	-0.187***	-0.189***
	(0.024)	(0.046)	(0.025)	(0.053)
Surface water: oxygen deficits	0.036*	-0.022	0.080***	0.014
	(0.019)	(0.034)	(0.022)	(0.040)
Floods	-17.389***	-15.529***	-23.296***	-22.770***
	(1.362)	(2.478)	(1.611)	(2.862)
Cooling degree days	1.020***	4.686***	1.011**	5.765***
	(0.377)	(1.236)	(0.444)	(1.433)
Heating degree days	-0.631***	0.350	-0.715***	0.745
	(0.132)	(0.439)	(0.154)	(0.500)
Wildfires	2.845***	1.053	2.594***	0.606
	(0.591)	(0.654)	(0.697)	(0.795)
One var at a time	X		X	
All vars at once		X		X

Note: table shows beta coefficients. Each observation represents a county × year. Housing data cover decennial census years 2000 and 2020; population data cover years 2003 and 2019. Each externality represents its value in the year 2003 (or, for wildfire and flood risk, the time-invariant county values). Cooling and heating degree days are in thousands. Parentheses show standard errors clustered by county. Units are shown in Appendix Table 1. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 8: Are People and Housing Moving Towards Externalities? Extremal Values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Dependent variable: 100 × log 2003-2019 population growth							
Air pollution	0.001	—	—	—	—	—	-0.003
	(0.015)	—	—	—	—	—	(0.016)
Drinking water pollution	—	-0.109***	—	—	—	—	-0.121***
	—	(0.018)	—	—	—	—	(0.019)
Surface water pollution	—	—	-0.026	—	—	—	-0.036**
	—	—	(0.019)	—	—	—	(0.018)
Floods	—	—	—	-0.076***	—	—	-0.122***
	—	—	—	(0.021)	—	—	(0.023)
Heat	—	—	—	—	0.138***	—	0.192***
	—	—	—	—	(0.023)	—	(0.027)
Wildfires	—	—	—	—	—	0.003	0.008
	—	—	—	—	—	(0.018)	(0.018)
N	3,134	2,975	2,926	3,134	3,103	3,133	2,771
R^2	0.000	0.012	0.001	0.006	0.019	0.000	0.050
Panel B. Dependent variable: 100 × log 2000-2020 housing growth							
Air pollution	0.022	—	—	—	—	—	0.013
	(0.015)	—	—	—	—	—	(0.017)
Drinking water pollution	—	-0.121***	—	—	—	—	-0.121***
	—	(0.019)	—	—	—	—	(0.019)
Surface water pollution	—	—	-0.013	—	—	—	-0.024
	—	—	(0.019)	—	—	—	(0.019)
Floods	—	—	—	-0.069***	—	—	-0.117***
	—	—	—	(0.020)	—	—	(0.022)
Heat	—	—	—	—	0.129***	—	0.188***
	—	—	—	—	(0.024)	—	(0.029)
Wildfires	—	—	—	—	—	-0.014	-0.007
	—	—	—	—	—	(0.019)	(0.018)
N	3,133	2,972	2,926	3,133	3,102	3,132	2,771
R^2	0.000	0.015	0.000	0.005	0.017	0.000	0.048

Note: table shows beta coefficients. Each observation represents a county. Each independent variable is an indicator for whether a county is in the top decile for a given externality. Each column of each panel shows a separate regression. Parentheses show robust standard errors. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 9: Inequality and Environmental Externalities, Sensitivity Analysis

	Poor (%)		Black (%)		Hispanic (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution:	0.37***	-0.04	1.77***	-0.03	-0.50**	0.20***
$PM_{2.5}$ monitors	(0.07)	(0.03)	(0.16)	(0.03)	(0.21)	(0.04)
N	1,160	2,501	1,160	2,496	1,160	2,496
Air pollution:	0.08**	0.14***	-0.63***	0.01	1.02***	-0.10***
ozone model	(0.04)	(0.02)	(0.06)	(0.01)	(0.13)	(0.02)
N	3,107	6,218	3,107	6,214	3,107	6,214
Drinking water:	0.07***	0.00	-0.02	0.00	0.14***	0.00
federal violations	(0.01)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)
N	3,124	9,377	3,124	9,367	3,124	9,367
Surface water:	0.07***	0.00	0.25***	0.00	-0.02	0.00*
oxygen deficits	(0.01)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
N	2,906	3,570	2,906	3,570	2,906	3,570
Floods	1.07	-0.11***	-18.28***	0.01	-21.93***	0.14***
	(0.80)	(0.04)	(1.39)	(0.02)	(1.29)	(0.03)
N	3,135	9,520	3,140	9,417	3,140	9,417
First Street	0.67***	—	-0.05	—	-0.79***	—
flood index	(0.16)	—	(0.35)	—	(0.28)	—
N	3,133	—	3,134	—	3,134	—
Cooling degree	0.29***	0.09***	0.86***	-0.01	0.50***	-0.06***
days	(0.01)	(0.01)	(0.04)	(0.01)	(0.05)	(0.01)
N	3,103	9,313	3,103	9,309	3,103	9,309
Heating degree	28.65***	8.81***	86.49***	-1.47	49.80***	-6.06***
days	(1.36)	(1.37)	(3.58)	(1.10)	(4.55)	(1.14)
N	3,103	9,313	3,103	9,309	3,103	9,309
Wildfires	-0.23	0.07*	-3.20***	0.02**	4.32***	0.00
	(0.19)	(0.04)	(0.50)	(0.01)	(0.76)	(0.06)
N	3,135	9,418	3,136	9,408	3,136	9,408
Year FE		X		X		X
County FE		X		X		X
Panel		X		X		X

Notes: each table entry shows a separate regression of the indicated demographic variable on the indicated externality. Each observation in odd columns is a county; each observation in even columns is a county × year. Standard errors clustered by county are in parentheses. Units are listed in Appendix Table 1. Asterisks indicate p-value less than 0.01 (***), 0.05 (**), 0.10 (*).

Appendix Table 10: Willingness to Pay for Environmental Externalities

	Air Pollution	Floods	Heat	Cold	Wildfires	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Annual willingness to pay ($mn county total)						
Mean	104.00	35.80	7.10	34.70	4.37	186.00
Std. dev.	(301.00)	(106.00)	(39.90)	(94.20)	(57.70)	(521.00)
Median	32.80	10.50	0.81	10.90	0.11	60.10
5th pctile	2.48	0.00	0.00	0.83	0.00	5.90
95th pctile	417.00	148.00	22.70	141.00	8.47	764.00
Panel B. Annual willingness to pay ($ per capita)						
Mean	1,202	384	70	518	35	2,210
Std. dev.	(455)	(196)	(83)	(309)	(117)	(566)
Median	1,173	365	32	528	4	2,216
5th pctile	509	0	0	40	0	1,283
95th pctile	1,957	715	238	1,035	149	3,111
Annual natl willingness to pay ($mn)	324,000	111,000	22,100	108,000	13,600	579,000

Notes: Each observation represents one county. Panel B shows unweighted mean across counties.

Appendix Table 11: Counties with Greatest Counterfactual Changes Due to Turning Off

		Improvement in Amenities (% of baseline GDP)	Nominal Wages (w) (%)	Prices (P) (%)	Real income (w/P) (%)	GDP (wl/P) (%)	Population (l) (%)
		(1)	(2)	(3)	(4)	(6)	(7)
Panel A. All Externalities							
Boise	ID	19.86	-1.15	0.10	-1.24	73.65	75.66
Sierra	CA	14.61	-1.16	0.31	-1.46	60.10	61.98
Park	CO	11.55	-0.90	0.11	-1.00	54.60	55.99
Panel B. Extreme air pollution							
Glascock	GA	15.94	-0.56	-0.05	-0.51	36.93	37.71
Taliaferro	GA	14.09	-0.54	-0.04	-0.50	34.72	35.45
Pope	IL	13.95	-0.50	-0.03	-0.47	31.91	32.57
Panel C. Extreme flood risk							
Hinsdale	CO	4.86	-0.59	0.01	-0.60	30.97	31.74
Sierra	CA	4.89	-0.42	0.05	-0.47	20.22	20.73
Hamilton	NY	4.30	-0.38	0.05	-0.43	18.06	18.51
Panel D. Extreme heat							
La Paz	AZ	2.09	-0.08	-0.01	-0.08	4.27	4.36
San Jacinto	TX	2.20	-0.06	-0.02	-0.04	3.78	3.85
Echols	GA	1.39	-0.06	-0.01	-0.05	3.45	3.52
Panel E. Extreme cold							
Ontonagon	IL	7.22	-0.33	-0.04	-0.30	20.38	20.78
Mineral	MT	6.94	-0.31	-0.02	-0.30	18.51	18.89
Meagher	MT	4.65	-0.30	-0.02	-0.28	17.72	18.07
Panel F. Extreme wildfire risk							
Boise	ID	10.19	-0.73	-0.01	-0.72	39.02	40.04
Sierra	CA	4.34	-0.38	-0.01	-0.37	18.80	19.25
Catron	NM	4.62	-0.35	0.00	-0.35	17.28	17.69

Notes: each panel shows the counties with highest percent increase in population in each of the six counterfactual scenarios