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Heat has larger impacts on labor in poorer areas*

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Abstract

Hotter temperature can reduce labor productivity, work hours, and labor income. The effects of heat are likely to be a joint consequence of both exposure and vulnerability. Here we explore the impacts of heat on labor income in the US, using regional wealth as a proxy for vulnerability. We find that one additional day >32 °C (90 °F) lowers annual payroll by 0.04%, equal to 2.1% of average weekly earnings. Accounting for humidity results in slightly more precise estimates. Proxying for wealth with dividend payments we find smaller impacts of heat in counties with higher average wealth. Temperature projections for 2040–50 suggest that earnings impacts may be 95% smaller for US counties in the richest decile relative to the poorest. Considering the within country distribution of vulnerability, in addition to exposure, to climate change could substantially change estimated within-country differences between the rich and poor in income losses from climate change.

Introduction

Whether climate change generally harms the poor more than the rich—and if so, why—is an important unresolved question. Accounting for distributional consequences is important for estimating the total welfare impacts of climate mitigation [1] as well as for understanding which potential forms of climate adaptation [2] could reduce impacts most equitably. Many of the integrated assessment models used to assess climate damages have either assumed a representative global agent or characterized damage heterogeneity across regions or countries [3], despite the fact that accounting for within-region and -country heterogeneity may affect the implied social cost of carbon substantially [4]. Few studies to date have estimated the potential distributional consequences of climate change *within* countries [5, 6].

Here we show that exposure to increased temperatures reduces labor income and measure how these impacts vary according to estimates of local wealth across counties within the US. We find substantial variation in impact along the estimated wealth distribution (figure 1(a)). While our analysis cannot resolve the mechanisms that give rise to the heterogeneity in damages, it suggests that if two regions each experience an additional hot day, the negative effect of that hot day on labor income is likely to be larger, on average, in the poorer region. Hence, taking within-country impact heterogeneity into account may be important for climate policy.

It has long been recognized that relative damages from environmental hazards, climate change among them, can be characterized as a function of relative exposure and vulnerability [7, 8], where exposure refers to the size of a temperature (or other) shock, and vulnerability refers to factors, such as housing stock quality, that mediate

* **One Sentence Summary:** Wealth moderates the negative income effects of heat.

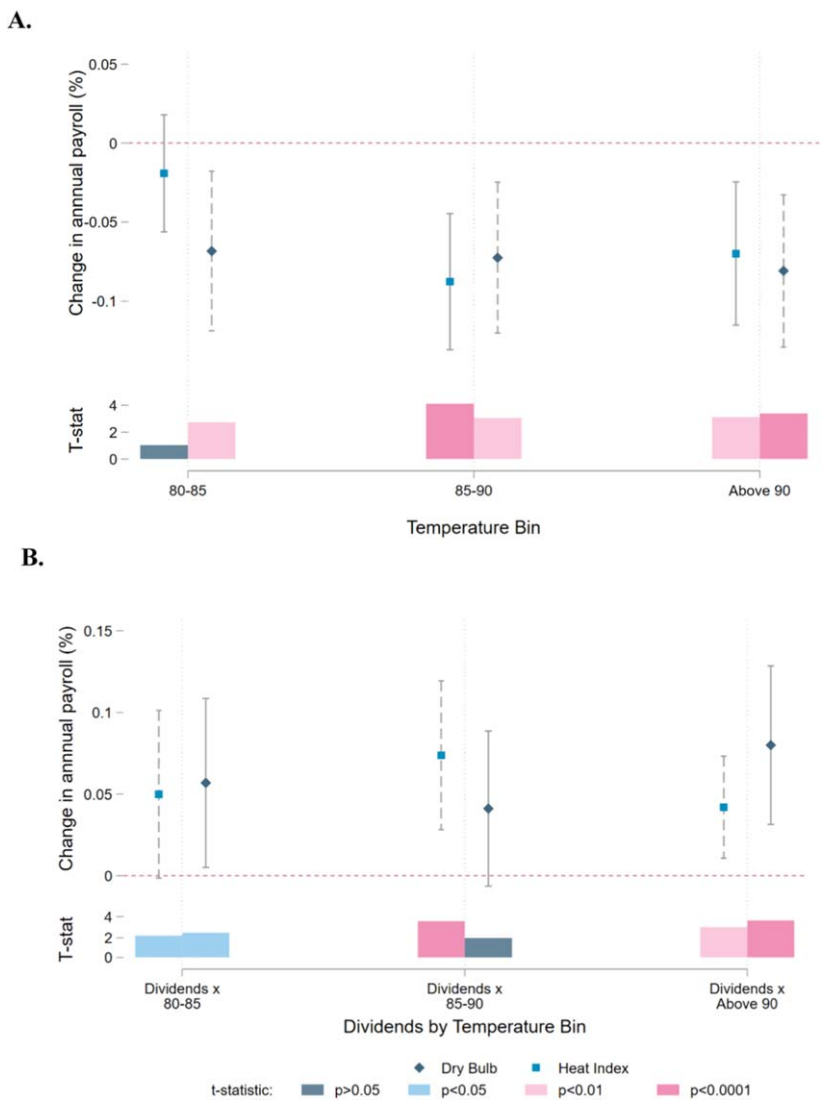

Figure 1. Impacts of heat on labor income: In (A), light blue squares represent the estimated percent change in annual payroll for every additional day in the dry bulb temperature bin identified on the *x*-axis relative to a day in the 15.5 °C–18.3 °C (60–56 °F) bin. So each additional day above 32 °C (90 °F) dry bulb reduces payroll by 0.07%. Dark blue diamonds represent estimates using the heat index. 95% confidence intervals are shown in light grey (solid lines for dry bulb and dashed for heat index). Bars at the bottom of the figure indicate the t-statistic on the coefficient and the shading of the bars indicates the p-value of the t-statistic for our estimates. In (B), squares again represent dry bulb temperature and diamonds heat index but here we report the coefficient on the interaction of dividends with temperature bins. The interaction indicates the change in the impact of an additional day in the temperature bin on the *x*-axis for every $1,000 increase in the county average level of per capital dividends. A county with $0 per capita dividends would be predicted to experience the full impact indicated in (A) while a county with $1,000 in per capita dividends would be predicted to experience a reduction in annual payroll of only 0.02% for each day above 32 °C dry bulb. Full regression results are shown in SI table 1.

the relationship between that temperature shock and realized temperature stress and welfare:

$$\text{Impact} = \text{f(Exposure, Vulnerability)}.$$

Literature suggests that both factors may cause climate change to harm the poor more than rich. At a country level exposure may be higher because, for example, poorer countries are likely to experience more extremely hot days for a given increase in global temperatures [9]. Vulnerability is higher, for instance, if poorer countries are more dependent on agriculture that is highly sensitive to climate [10–12] or have fewer resources to devote to adaptive investments such as air conditioning (AC) [13, 14].

While cross-country studies of temperature and economic output find that poorer countries' production is more susceptible to heat [15–17], few studies examine how the within country distributions of exposure and vulnerability effect estimates of heat's impact. One existing study that does examine how the marginal impact of heat varies across the wealth suggests that the marginal impact of heat on per capita GDP does not vary substantially by wealth levels but less wealthy areas are more exposed to high temperatures [6]. Other existing work has relied on this difference in expected warming alone—i.e. the fact that a given unit of climate change

globally will lead to a larger increase in dangerously hot days in some areas than others—to document substantial distributional consequences [3, 18]. As we point out above, examining only the impact of differences in exposure across the income distribution ignores the contribution that differences in vulnerability may make to exacerbating the distributional consequences of climate change.

It is unclear how accounting for both vulnerability and exposure may change these within-country distributional consequences, particularly with regard to effects on labor income. Evidence in the context of health and human capital impacts suggests that vulnerability may vary substantially within countries [19, 20]. In many parts of the world, baseline and projected changes in exposure also vary substantially within countries. Regressive impacts within countries may be driven by differences in exposure as market forces such as residential sorting [21] lead the poor to live in places that are more exposed to warming [22]. But the poor may also be more vulnerable due to factors such as housing quality, health, or time spent outdoors working that tend to be correlated with poverty. On the other hand, it is possible for the rich to be more exposed to some climate impacts, such as property damage due to storms [3]. The total impact of climate change will thus be determined by the joint distribution of exposure and vulnerability across populations within a country. As a result, measuring changes in exposure is not sufficient for determining which populations will be most impacted by future changes in climate.

In order to estimate the heterogeneity in heat-driven income changes across a wealth distribution we combine US county-level payroll and temperature data [23] with per capita dividend payments. Dividend payments are highly correlated with the size of underlying stock holdings and thus act as a proxy for the average wealth of a county [24]. This provides an estimate of the correlation between the average wealth in a county and the marginal impact of a hot day on labor income. Because wealth and poverty levels are often highly correlated, we can also estimate a gradient between poverty levels and the marginal impact of a hot day.

How much might accounting for vulnerability in the estimates of climate damages matter? We attempt to illustrate the importance of jointly considering exposure and vulnerability by considering the impact of our estimates in the context of projected changes in temperature. We examine how estimates of wage losses in US counties with high and low poverty under RCP6.0 change when we account only for exposure versus for exposure and vulnerability jointly. We also highlight that the spatial distribution of vulnerability and temperature exposure can vary substantially across countries. In the US for example we find that poverty and changes in exposure to hot days are positively correlated. Areas with less poverty will experience fewer hotter days in the future. However, when we examine a set of six countries for which sub-national poverty data are available, we find that in some cases poverty rates and exposure are anti- correlated. Areas with less poverty are exposed to the same or more hot days as poorer areas in some countries. This variation in the spatial relationship between exposure and our measures of vulnerability across countries highlights the importance of considering both exposure and vulnerability when estimating the future damages of climate change. Failure to do so may lead to substantial underestimation of the differences in the impact of climate change across the income distribution.

The impact of heat on labor income

Within the US, we estimate that across all US counties from 1986–2011, one additional day with dry-bulb temperatures >32 °C (90 °F) reduces non-agricultural payroll by 0.04%. Ambient heat matters for human performance because it reduces the ability of the body to cool itself by conducting heat to the skin [25]. However, the efficiency of this process is determined by the combined effect of heat, humidity, and wind speed [26]. Consistent with the true impact of heat varying with humidity, when we incorporate humidity into our measure of temperature in the form of a heat index we observe slightly larger point estimates (figure 1) [27].

The implied magnitude is a reduction in average weekly pay of ~2.2% per >32 °C (90 °F) day, though our data does not allow us to determine whether these effects are due to reductions in labor supply, labor productivity, labor demand, an increase in firm costs, or some combination of all of these. Because we use annual variation in temperature, these estimates are net of intra-annual adaptations including inter-temporal labor substitution, where workers and firms may attempt to make up for lost productivity during a hot day or week on a cooler day or week within the same year. We do not document significant impacts of cold temperature on payroll though estimates are substantially noisier (see SI table 1 (available online at stacks.iop.org/ERC/3/095001/mmedia) and SI figure 1 for full results).

Marginal effects of hotter temperature on earnings are more negative in less wealthy US counties. Higher levels of per capita dividends are correlated with a meaningful reduction in the marginal damages of an additional 32 °C (90 °F) day using both dry bulb temperature and heat index. To account for the fact that dividend payments may be mechanically correlated with temperature shocks (e.g. if firm profits are adversely affected by local temperature, and stock portfolios are home-biased), we prefer a measure of five-year average dividends, and find that the effects are robust to this specification (see SI table 2 for alternative measures of

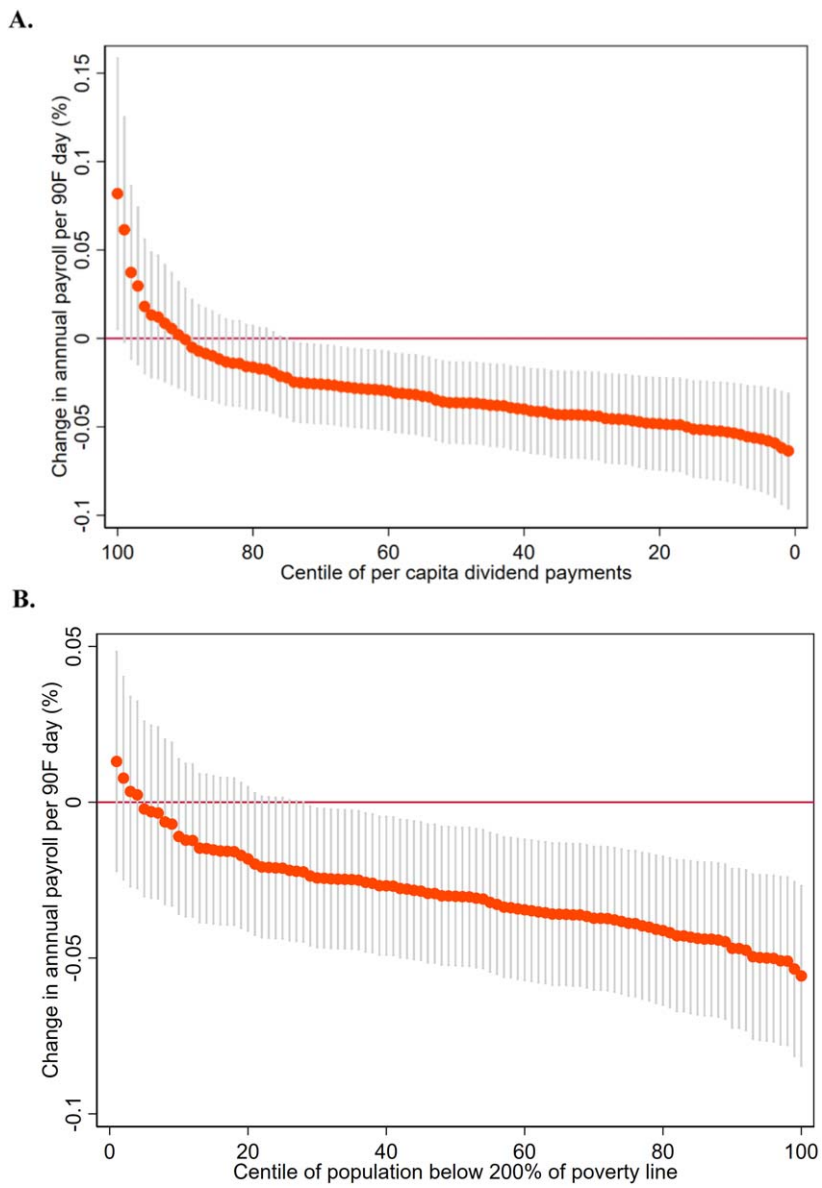

Figure 2. Change in heat impact by wealth and poverty: Red dots represent marginal effects of an additional day >32 °C (90 °F) adjusted by county wealth equaling ($\beta_{DA90} + Dividends \times \psi_{DA90\times\eta} \times DA90$, where β_{DA90} and $\psi_{DA90\times\eta}$ are the estimates for the impact of days above >32 °C (90 °F) and the reductions in that impact for each $1,000 increase in per capita dividends show in figures 1(a) and (b). β_{DA90} is reported in 1a while $\psi_{DA90\times\eta}$ is reported in 1b. Each dot represents average dividends received across 30 counties. Grey bars represent standard errors using the delta method. In both figures the wealthiest counties are on the left. (A) shows the change in the marginal effect by centile of dividend payments. The first centile has a mean dividend payment of $100, the 100th $4,000. (B) shows changes in marginal effects by poverty rate, measured as population share living under 2× the US federal poverty line. The first centile has a mean poverty share of 13%, the 100th 69%.

dividends). Increasing per capita dividends from $0 to $1,000 (slightly more than the mean dividends received in our sample) reduces the impact of an additional day >32 °C (90 °F) by about three quarters.

Figure 2(a) shows how the marginal impact varies as one moves down the observed regional wealth distribution (see SI figure 2 for maps of dividend payments across the US over time). The negative payroll impact of a day >32 °C (90 °F) persists until around the 90th centile of the distribution. This suggests that areas that are wealthier, on average, experience smaller marginal reductions in aggregate labor income for the same increase in hot days. Because we do not have data on individual income and wealth, it is not possible for us to determine whether the relationship we document is due to different sensitivities between rich and poor individuals or variation in neighborhood-level factors across richer and poorer regions or both [28]. We believe this constitutes an important area for future research.

Our measure of wealth is closely related to the number of people in an area in poverty. Figure 2(b) shows the marginal impact of a day >32 °C (90 °F) in counties ordered by the share of the population living under 200% of the US federal poverty line. We estimate that the marginal impact of an additional hot day on payroll in counties with the highest poverty rate is ~five times the impact in counties with the lowest poverty rates. Though we

Table 1. Average Annual US Payroll Losses 2040–50.

	Days over 32 °C	Naïve Loss (%)	Adjusted Loss (%)	Ratio (Adjusted Loss/ Naïve Loss)
Poor	94.4	-4.0	-4.8	1.2
Rich	41.2	−1.8	-0.2	0.1
Difference	53.2	-2.3	-4.6	

Column (2) calculates mean lost payroll over the decade 2040–2050 assuming the warming projected under RCP6.0 without adjusting for poverty, column (3) adjusts for counties' wealth. Poor counties are the 10% of counties with the highest fraction of the population below 200% the federal poverty line, rich with the smallest, calculated based on the average of 1990, 2000, and 2010 poverty rates.

cannot estimate the direct correlation between temperature impacts and poverty over time in the same way we do with dividends because poverty data is not available at high enough frequency, we take these results as suggestive of similar differences in vulnerability.

Damages from projected climate change within the US

As an illustrative exercise we take projections of dry-bulb temperatures under Representative Concentration Pathway (RCP) 6.0 and compare projected annual averages from 2040–50 with a historic baseline from 1986–2011. Between 1986–2011, the average US county experienced 35 days >32 °C (90 °F) per year. Under RCP6.0 that number rises to 67 in 2040 and 75 in 2050. Absent further adaptation, this translates into large earnings reductions, especially for poor counties. Total reduction in payroll in the poorest decile of counties is expected to be around 4.8% per year from 2040–50 compared to no impact in the richest decile (table 1). Poor counties are projected to experience more warming—by 2050 they will suffer over twice as many days >32 °C (90 °F) as rich counties—and appear more vulnerable to heat at baseline. The contribution of higher vulnerability becomes evident when comparing unadjusted payroll losses from table 1 to adjusted ones, where the latter allows for heterogeneity in marginal damages across counties by historical poverty rates.

Figure 3 illustrates table 1's results graphically. Counties with a higher share of the population living below the poverty rate will experience more hot days than counties with lower population shares below the poverty rate (exposure). They also appear to be more vulnerable; i.e., marginal damages from a given increase in temperature appear to be greater on average in counties with more poverty, despite the fact that many poor counties are in already hotter parts of the country, where one might expect greater levels of adaptation. Figure 3(a) shows the average annual payroll loss in percentage terms from 2040–50 by the average number of days >32 °C (90 °F) in each centile. The solid line, adjusted for heterogeneity by area wealth, is steeper than the unadjusted, dashed line, suggesting that failure to account for how impacts change with wealth levels underestimates the effect of increasing the number of hot days in the hottest areas. Figure 3(b) shows the same trends plotted by poverty centiles. Here too, using only differences in exposure (dashed line) overestimates projected damages at low levels of poverty and underestimates them at high levels of poverty, relative to adjusted losses (solid line).

Several caveats are worth noting. Our projections are meant to provide illustrative comparisons of *relative* impacts, not predictions of absolute climate damages. To simplify the analysis, we hold poverty rates, wealth, and industrial composition fixed at current levels, and assume marginal impacts remain the same over the next three decades (i.e., we do not account for adaptation over time). If there is convergence in poverty levels across counties within the US, these relative estimates would be overstated. If, on the other hand, inequality across counties rises secularly, they may understate the differences. In our data relative poverty rates have remained stable from 1990 to 2010. However, if economic growth enables poorer counties to achieve the same level of protection (adaptation) by 2040–50 that rich areas exhibit today, the differences we estimate may also be overstated. Finally, earnings impacts may be different from changes in welfare for a number of reasons: for instance, if reduced payroll is driven by reduced labor supply and increased leisure time. Future research ought to further decompose these findings.

Global implications

Our analysis suggests that vulnerability to the negative impacts of heat varies substantially within the US. Estimates of projected damages accounting only for differences in exposure appear to underestimate the difference in impacts between the rich and poor. This may also be true in other countries. In the US, exposure and vulnerability appear to be positively correlated: areas that are expected to experience greater heat exposure

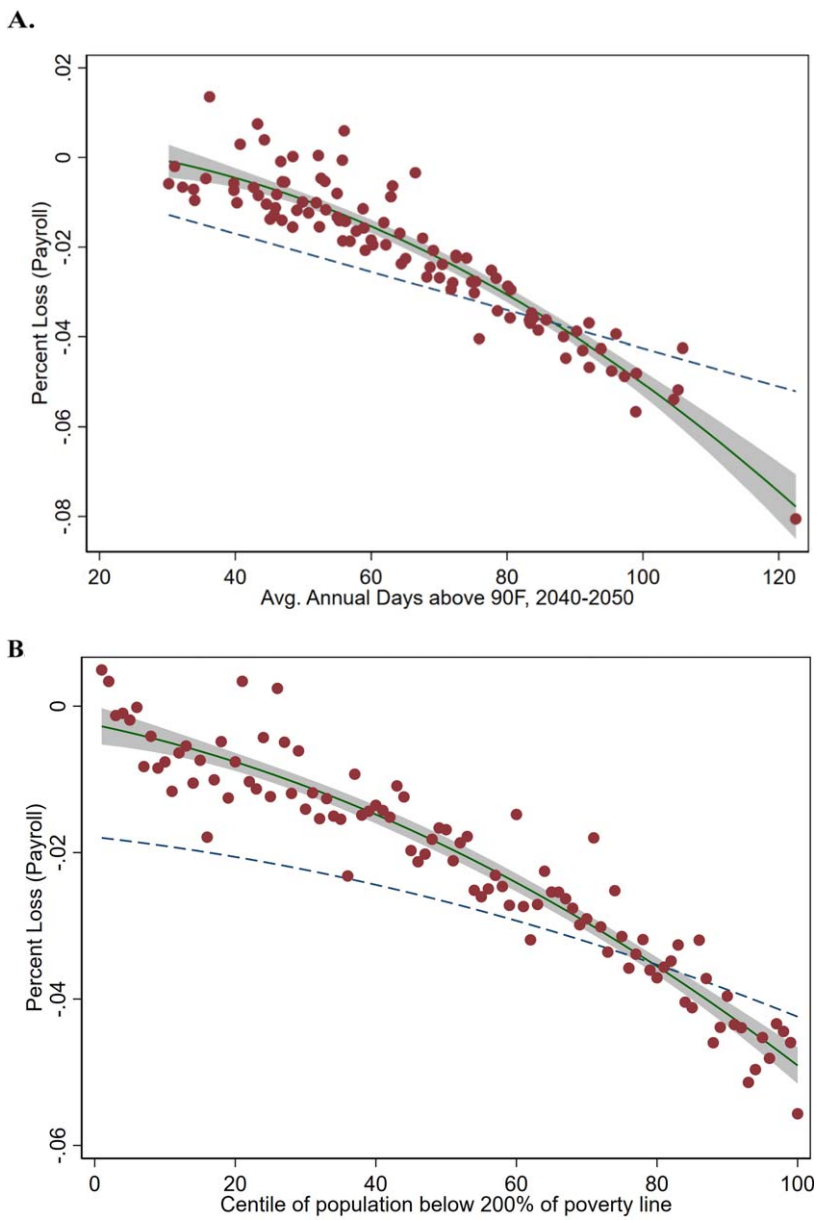

Figure 3. Projected future with and without accounting for vulnerability: US average annual percentage loss in payroll from 2040–50, calculated as $DA90 \times \beta_{DA90}$. Maroon dots show average lost payroll by centile considering both exposure and vulnerability. Each dot represents average dividends received across 30 counties. Solid green lines show quadratic best fit, with 95% confidence intervals in grey. Dashed blue lines are the quadratic best fit lines of the damages only considering exposure. (Maroon dots corresponding to this line are omitted.) (A) graphs averages within poverty centiles against the average number of days >90 °F annually from 2040–50. (B) graphs them by the share of the population living under 200% of the federal poverty line.

also tend to exhibit greater vulnerability. While the theory of residential sorting on local amenities might suggest this to be true generally [21, 22], in some countries, other correlated factors such as differences in agricultural yield or proximity to valuable mineral resources or trading ports might lead to the reverse pattern of sorting.

To highlight the importance of considering vulnerability and exposure jointly, we collect temperature projections for 2040–2050 based on RCP6.0 for six countries (India, Indonesia, Mexico, Morocco, Mozambique, and Nigeria) for which sub-national poverty rates from the World Bank are available. We then measure the gap in projected exposure between high and low poverty districts of these countries. 'Districts' here differ across countries, corresponding to 'Admin 1 units' in all countries except Indonesia, in the US this would be states. In Indonesia we have poverty data at 'Admin 2' levels, which would be US counties.

We can compare these expected differences in exposure by poverty level to what we measure in the United States, where the rich will be exposed to 50 fewer days >32 °C than the poor. In some countries such as Morocco and Indonesia, the low poverty (wealthier) areas appear more exposed to extreme heat than high poverty (poorer) areas, though it is possible that more spatially resolved data would reverse this pattern (SI table 3). In others, such as India, the gap in exposure between high and low poverty is of the same direction but is significantly smaller than in

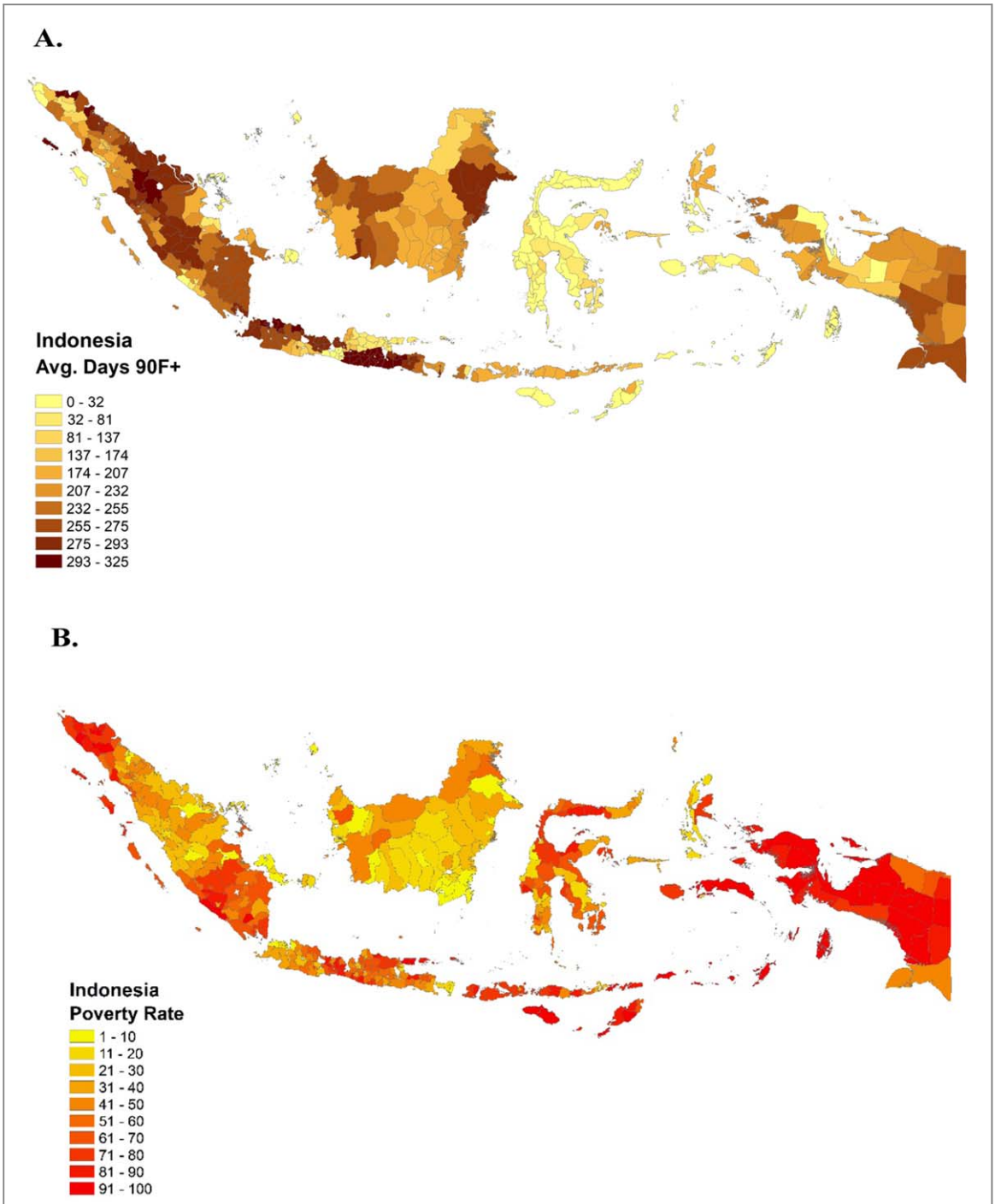

Figure 4. Comparison of exposure and vulnerability in Indonesia: (A) shows the areas expected to see the largest number of days per year over 90 °F under RCP6.0 from 2040–2050. (B) shows poverty by district at the Admin 2 level.

the US. In figure 4 we show the geographic distribution of expected heat exposure and poverty for Indonesia, the country for which we have the most geographically resolved data. Jakarta is a good example of the spatial patterns that make considering vulnerability important when estimating future damages of climate change. The region around Jakarta is expected to be increasingly hot relative to the rest of Indonesia but has relatively low poverty ratios. Considering exposure alone would suggest Jakarta suffer relatively larger damages from climate change driven increases in heat as compared to poorer but cooler regions of Indonesia. However, that ignores the likelihood that residents of Jakarta, because of their increased wealth, may be better positioned to mitigate the negative consequences of heat than residents of cooler but poorer areas. Indeed, if one makes the heroic assumption that the gradient in impacts between high and low poverty areas that we measure in the US approximates that in Indonesia, accounting for vulnerability increases the difference in the losses suffered by the wealthy and the poor by 12.2 percentage points. This occurs because the past patterns of settlement in Indonesia mean that, in contrast to the US for example, Indonesia's hottest regions tend to be richer than average.

This exercise is subject to numerous caveats and limitations. Marginal damages are unlikely to map directly from the US to other countries, given vastly different demographic and industrial composition. The point of this exercise is to illustrate that failure to account for differing vulnerability, in addition to differing exposure, could lead to potentially significant mis-estimation in relative impacts between richer and poorer regions. The magnitude of this misestimation will depend on how much more the wealthy are protected than the poor from the impacts of heat in other countries. The differential we measure in the US may overstate the differences in other countries if even the wealthiest individuals in poorer countries cannot afford access to AC or work in highly exposed industries. It may understate the differential if even the poorest households in the US own AC, whereas those in less developed countries do not. Our estimates also understate the differential to the extent that our US estimates omit agricultural income, which is likely to be highly impacted and is the major source of income for the poorest in other countries.

Discussion

The poor appear to be more vulnerable to a given unit of heat exposure than the rich. If they also tend to live in areas that are expected to experience greater increases in temperature from climate change, the net effect may be highly unequal impacts for a given level of average warming globally. Our analysis highlights the importance of accounting for heterogeneity in vulnerability to climate change within as well as across countries [3, 15, 17, 29–33]. Here we focus on differing impacts across counties within the US, in the past (figure 1) and extrapolated into the future figure 3 and table 1).

Explanations for differences in marginal impacts of heat exposure typically center around the presence of adaptive investments, notably AC, or past experience with extreme heat. Our analysis builds on these explanations by illustrating the variation in heat-related wage losses across the local wealth distribution, and comparing this to variation arising from differences in expected warming. While we find that controlling for the share of houses in a county with some form of residential AC lowers the correlation between impacts of heat exposure and wealth slightly, wealth still plays a significant role in mitigating the impact of heat on payroll (SI table 4), perhaps indicating the importance of other, non-AC adaptations.

We also present results restricting our analysis to only labor income in highly exposed industries, based on the observation that a given increase in ambient temperature may lead to greater realized exposure for certain workers (e.g. landscapers, construction workers, highway maintenance crews). SI table 5 shows that wealth is still correlated with reductions in the impact of heat exposure but it is no longer significant. This is consistent with the idea that in wealthy areas a larger share of workers work in non-exposed industries and this reduces their vulnerability to heat. Consistent with this possibility, we find a negative correlation between county average wealth and the share of county payroll from highly exposed industries.

Our results are consistent with the hypothesis that even in non-agrarian, developed countries the poor may face obstacles to climate adaptation. There is suggestive evidence from recent microeconomic studies that AC ownership and use are tightly correlated with income [34, 35]. Moreover, there is evidence that poorer individuals may face liquidity constraints in purchasing energy-intensive appliances [13], and that poorer school districts have less school AC, even within the same region [20].

Failure to accurately estimate the vulnerability gap may be especially problematic for persistent climate impacts like heat exposure. As earnings losses from heat exposure are annual (and net of intra-annual time reallocation), cumulative effects of even a small gap in marginal impacts can be substantial. The 4.8% adjusted annual loss for the poorest US decile over the ten years from 2040–50 (table 1) amounts to losses of nearly half a year's pay over the decade, compared to one tenth of a year's pay for the richest decile.

The relationship between wealth levels or poverty rates and marginal damages should not be interpreted causally, as they may be driven by other factors correlated with dividend payments (wealth) or poverty rates. Our results limiting the sample to highly exposed industries suggest that at least some of the difference in vulnerability is attributable to differences in occupations that are correlated with wealth. Similarly, our measure of wealth does not allow us to distinguish between the role that wealth stocks versus increased cash-flow derived from that wealth may play in reducing the impacts of heat. Our results simply indicate that the wealthy appear less vulnerable to heat than the poor. This is likely due to the joint impact of many advantages—higher educational attainment, different occupational choice sets, and easier ability to finance adaptive investments—that the wealthy enjoy. Lastly, our projections of future impacts do not explicitly include further adaptation, instead assuming a level of adaptation similar to the average of the period between 1986 and 2011. As the incidence of extreme heat increases, societies may adapt to reduce the impact of exposure [2, 14, 23, 36, 37]. Incorporating adaptation would lower the absolute impact of heat. However, it is unclear how incorporating adaptation into estimates of future impacts would affect the gap in vulnerability between the rich and poor. If the

rich adapt more quickly, including adaptation would increase our observed gap, and vice versa. To the extent that adaptation is correlated with wealth, adaptation alone is unlikely to eliminate the gap we estimate.

Materials and methods

We measure both the aggregate non-agricultural payroll received in nearly every county in the contiguous US from 1986–2011 [23] and proxy for counties' wealth from 1989–2011. We combine these data with daily resolution weather data supplemented by historic humidity data. For illustrative future extrapolation, we rely on RCP6.0. For illustrative non-US estimates, we use World Bank data on poverty at the Admin 1 & 2 levels and RCP6.0.

Payroll data

Annual US payroll data for 1986–2011 are from the County Business Patterns database, by 5-digit North American Industry Classification System (NAICS) codes. We match Standard Industrial Classification (SIC) codes prior to 1997 to NAICS based on Census crosswalks. Payroll includes salaries, wages, commissions, dismissal pay, bonuses, vacation allowances, sick-leave pay and employee contributions to qualified pension funds.

Daily weather data

We combine our measures of output with two measures of temperature: daily maximum temperatures over the contiguous US at 4×4 km resolution for 1981–2016 obtained from PRISM Climate Group, and future temperature projections downscaled from the CMIP5 global model [38]. The latter reports daily temperature maxima, minima and total daily precipitation in a $1/8°$ grid covering the continental US. We overlay both grids on county boundaries defined in the 2010 US census. We match grid points to counties in ArcGIS where matches are defined by whether a county contains a point. For counties that contain no points we average over the ten nearest points using inverse distance weights.

We calculate heat index based on using daily maximum temperatures and maximum vapor pressure deficit over the contiguous US at 4×4 km resolution for 1981–2016 obtained from PRISM Climate Group [27]. In the main analysis we maintain a threshold of 90 °F (equal to 32.22 °C, and rounded to 32 °C in the main text) when using both dry bulb and heat index, largely for consistency with the existing literature, which is largely published in US economics journals, utilizing the Fahrenheit threshold. Noting, however, that 90 °F dry bulb is a different threshold than 90 °F heat index we present results in SI table 6, where we attempt to maintain a comparable threshold. We use the IPSL-CM5-LR CMIP5 model [39] for global projections, using daily max temperatures for $1.875 \times 1.875°$ and matching grid points to country Admin 1 units using a spatial join procedure in ArcGIS.

Dividend data

We proxy for wealth by county with annual dividend payments and returns filed from county income tax files reported by the US Internal Revenue Service's (IRS) Statistics of Income (SOI) from 1989–2011. We take the number of returns as the population of taxpayers in the county in that year and calculate per capita dividends as the dividend payments divided by the number of returns. As the rate of income generation is constrained [40], variation in the size of dividend flows should proxy for variation in the underlying capital base, rather than e.g. investing skill. Using comprehensive data on wealth and dividends from Swedish tax records shows monotonically increasing dividend payments moving up the wealth distribution [24]. Data from the US Census bureau from the 2017 tax year indicates that stock holdings, both in and out of retirement accounts, is monotonically increasing with overall net worth as well as other measures (e.g. home equity) of wealth.

As many dividends will be paid out into tax-privileged retirement accounts, they may not be reflected in the data reported to the IRS and, there, not reflected in its SOI database. Our measure would, thus, not account for the value of tax-privileged retirement accounts. As these tax-privileged accounts typically have a withdrawal penalty and are, hence, not a liquid form of wealth, we believe these accounts should not be counted in a measure of wealth relevant to this study.

It is also worth noting that a substantial minority of the US population does not own stocks and so receives no dividends. Non-stockholders are disproportionately concentrated at the lowest end of the wealth distribution. Our approach will identify these individuals as having no wealth—correctly to the extent that stock holdings are a common form of liquid wealth. However, it seems likely that individuals who are marginally below the threshold for owning stock will have liquid wealth, for example, in the form of savings accounts that would allow them to invest in adaptation in a way that an individual with zero stock wealth and zero savings would not be able to. Our approach will pool these individuals and estimate a single effect for them as individuals with no measured wealth. As a result, our estimates of the marginal effect of heat on the poor are likely an underestimate of the effect that heat has on the truly poorest members of society—those with no liquid wealth at all.

Another important question is what measure of dividends should be used. For example, year to year variation in dividend payments may be more reflective of changes in company dividend policy than underlying wealth. On the other hand, a twenty-year average of dividend payments might better reflect real underlying wealth but would not account for changes in the wealth make-up of a county. Take the example of Detroit and Pittsburgh (SI figure 3). Pittsburgh has become a wealthier city over the time period in our sample, which is reflected in the trend in their dividend payments. Detroit, on the other hand, has become poorer. Looking across the entire country SI figure 2(a) shows the counties that received the most dividend payments in 1990. While the pattern of payments is generally stable over time (2010 payments are show in SI figure 2(b)), there are some shifts. For example, the dividend payments received in the manufacturing heavy Rust Belt states have declined in this time period, as would be expected. In general, the maps reflect a pattern where wealth in the central and upper Midwestern states, and northern New England, has declined. This is consistent with changes observed in broader measures of wealth from 1990 to 2010. We believe that any attempt to relate wealth to adaptive capacity should account for these changes over time. As a result, we prefer a four-year average that smooths out the year to year variation but still reflects trends in the wealth of a county.

The 2003 tax cuts

The way in which dividends are treated by tax law underwent a notable change in 2003 with the Bush tax cuts. Prior to 2003 all dividends were taxed at the prevailing marginal income tax rate. The tax cuts introduced a distinction between qualified and non-qualified dividends. Non-qualified dividends remain taxed at the income tax rate, but since 2003 qualified dividends have been taxed at a lower, 15% rate. One might be concerned that the new treatment of dividends induced attempts to classify other income as dividends in ways that would confound our results. We present graphical evidence in SI figure 4 that suggests there was no change in the size of dividend payments before or after the tax reform, pointing to there not having been a major reclassification of income. While dividend payments fluctuate and do decline substantially in the early 2000s before recovering, it appears that the driving factor is recessions rather than changes in the tax law. There also does not appear to have been a long-term effect of the tax law change with pre-2003 and post-2003 dividend payments averaging nearly exactly the same level.

As an additional robustness check we top-code the largest dividend receiving counties at the 99th percentile to ensure that our results are not driven by outliers (SI table 7).

Global poverty data

Global poverty come from the World Bank's estimates of poverty at subnational levels reported in the World Bank Databank. Admin 2 data on Indonesia comes from the World Bank's INDO-DAPOER database. Our results are based on the poverty head count ratio or the share of the population within an admin 1 unit living below a given threshold of poverty. We choose the national poverty line as the threshold as opposed to the rural or urban lines. Because poverty is measured relative to a national poverty line the poverty data is not comparable across countries. For example, the specific threshold in India is different than in Indonesia.

Analytic model

Here we present a framework that describes the relationship between wealth and vulnerability to heat. This framework informs our econometric approach but is not mathematically related. We assume a production function of the form:

$$Y_{it}(A,\, L) = Y_{it}(A(T_i^E,\, \omega_i),\, L(T_i^E,\, \omega_i)), \tag{1}$$

where T_i^E represents extreme temperature events in county (or, internationally, admin 2 unit) i, A is task productivity, L labor inputs, and ω_i wealth by i. We omit capital, assuming its marginal product is relatively unaffected by heat. This assumption does not require that firms are agnostic about climate in making decisions about where to locate capital. However, because we consider within location variation in temperature and payroll on an annual basis the long-term decision about where to allocate capital is beyond the scope of the model we consider here. We further assume that $\frac{\partial \mathrm{A}}{\partial \mathrm{T^E}} \leqslant 0$ and/or $\frac{\partial \mathrm{L}}{\partial \mathrm{T^E}} \leqslant 0$, such that in general extreme heat will have a non-positive impact on output: $\frac{\mathrm{dY(A(T^E), L(T^E))}}{\mathrm{dT^E}} \leqslant 0$, both by decreasing productivity and labor inputs [23]. Per equation (1), the impact of temperature by i is both a function of $\mathrm{T_i^E}$ and of ω. Increasing ω mitigating the impact of $\mathrm{T_i^E}$ would imply that wealth reduces the impact of temperature directly, $\frac{\partial^2 \mathrm{A}}{\partial \mathrm{T^E} \partial \omega} > 0$, and/or that wealth reduces the temperature sensitivity of labor inputs, $\frac{\partial^2 \mathrm{L}}{\partial \mathrm{T^E} \partial \omega} > 0$.

Greater wealth, in turn, reduces the impact of a given temperature realization by insulating labor productivity and supply against heat. It is, of course, possible that the poor may have a greater marginal utility of consumption, and thus increasing wealth may lead to a higher sensitivity of labor supply due to income effects.

In practice, it seems more likely that labor demand determines short-run labor inputs—particularly for exposed workers. Profit-maximizing firms, in turn, would reduce labor demand if extreme heat reduces productivity.

Empirical strategy

We utilize the variation within a given county i's exposure to extreme temperature T_i^E to identify the impact of exposure to T_i^E on productivity, proxied by payroll data for 1986–2011. For consistency with the existing literature we choose 90 °F (~32 °C) as the threshold [14, 23]. To account for spatial dependencies in temperature exposure of adjacent counties, we cluster standard errors at the state-by-year level. The base model is:

$$\ln(y_{ijt}) = \beta DA90_{ijt} + \psi(DA90_{ijt} \times \omega_{ijt}) + \sigma \boldsymbol{X}_{it} + \rho(\boldsymbol{X}_{it} \times \omega_{ijt}) + \delta_i + \gamma_t + \nu jt + \epsilon_{ijt}, \quad (2)$$

where y_{ijt} is log annual payroll in county i, state j, and year t. $\boldsymbol{X}_{it}$ is a vector of county-year specific controls, including number of days in 10 °F temperature bins from 0–90 °F excluding the 70–80 °F bin, number of days with max temperature below 0 °F, number of days with snow, and total annual precipitation in i and t. Parameters δ_i and γ_t are county and year fixed effects, ν_{it} is a state-by-year trend. ϵ_{ijt} is the error term.

Our variable of interest is $DA90_{ijt}$, the count of days >90 °F by i and t, and its interaction—denoted by ψ—with ω_{ijt}, the per capita wealth of county i in year t. Because we omit the 70–80 °F bin from our set of controls the coefficient β should be interpreted as exchanging a day in the 70–80 °F bin for one >90 °F. The total impact of a day >90 °F is the sum of β and $\psi \times \omega_{ijt}$. Thus, ψ can be interpreted as the reduction in the marginal impact of an additional day >90 °F of a one unit increase in per capita wealth.

Air conditioning (AC) penetration

Our measure of AC penetration is constructed from two primary sources. The first is the 1980 Census of Population which collected AC penetration rates at a county level. We use the reported penetration rates in 1980 as a basis and then extrapolate based on the region-level growth rate of central, window and total AC penetration recorded by the Energy Information Agencies Residential Energy Consumption (REC) surveys. The REC surveys provide penetration rates by region from 1980 to 2009 with a two or three-year frequency. We linearly interpolate growth rates for the missing years and assign counties their corresponding regional growth rate. Using this growth rate and the observed penetration rate in 1980 we create a measure of penetration in every county in each year from 1980 to 2011. We top-code penetration at 100%. Our primary specification uses the penetration rate of total AC but we conduct the same exercise for central and window AC and estimate all models with all three measure of AC penetration.

Highly exposed sectors

SI table 5 shows results on highly exposed sectors only. We use the National Institute of Occupational Safety and Health (NIOSH) classification for utilities, construction, agriculture, manufacturing, transportation, and mining as highly exposed to heat. We exclude agriculture from our analysis, where impacts of heat exposure are confounded by the direct effect of heat on agricultural output [10–12]. In the US 22% of workers are employed in such sectors [41].

Within-US projections

We use the following procedure to project damages into the future in the US. We hold the per capita dividend payments in a county constant at their 2011 value. We then calculate the number of days that county is projected to experience above 90 °F annually from 2040 to 2050. To calculate the naïve payroll losses, we multiple the projected number of days in a year by the estimated coefficient on β_{DA90} from Column 4 of table 1. To calculate the adjusted losses (accounting for vulnerability) we use $(\beta_{DA90} + \text{Dividends} \times \psi_{DA90\times\omega}) \times \text{DA90}$ where DA90 is the projected days above 90 °F in a given year, *Dividends* is the level of per capita dividends from 2011 and $\psi_{DA90\times\omega}$ comes from the specification in Column 3 of table 1. This adjusts the marginal damages of a day above 90 °F based on the level of wealth as measured in 2011. We then average adjusted and naïve losses within counties across the years from 2040 to 2050. Finally, we average the losses among the 10% of counties with the highest and lowest average poverty rates to determine the losses in the 'Poor' and 'Rich' counties that we report in table 1.

Data availability statement

Data to replicate the findings of this study are available from the authors upon request.

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