Inequalities in wildfire smoke avoidance

Edward A. Rubin[1,*] **and M. Steven Holloway**[2]

[1]University of Oregon, Department of Economics, Eugene, OR, USA
[2]Michigan Technological University, College of Business, Houghton, MI, USA
[*]email: edwardr@uoregon.edu

ABSTRACT

Humans can reduce risk exposure through short-term avoidance, but this strategy may not be equally accessible to all members of a population. We combine data from cellphone movements, satellite-based wildfire smoke plumes, and Census-reported demographics to document substantial heterogeneity and inequity in communities' tendencies to out-migrate to avoid smoke. Higher-income and whiter populations leave their counties at significantly higher rates during smoke events. These results suggest that the same populations who face social and environmental injustice on many other measures are less able to avoid wildfire smoke—underscoring equity concerns for wildfire damages and climate adaptation.

In the face of imminent danger, people often flee—avoidance is half of *fight or flight*. Recent IPCC reports highlight the importance of such adaptation on humanity's road to mitigating climate-change damages[1]. However, nothing guarantees individuals have equal access to this strategy. Recent research highlights the importance of avoidance behaviors for hazards like wildfire smoke[2]. Yet work on inequality in the US documents marked disparities consistent with unequal avoidance opportunities—life expectancy and mortality[3–8], health[9–11], healthcare[12–14], pollution exposure[15–19], educational opportunities[20–23], transportation[24], and employment outcomes[25–29]. Indeed, many of these dimensions of inequality represent mechanisms that affect individuals' abilities to flee (liquidity, job security/benefits, access to transit) and/or consequences of unequal opportunities to relocate (health and life expectancy). If less-privileged communities are less able to avoid hazards like wildfire smoke, existing inequities may worsen.

Wildfire smoke is an increasingly important and pervasive hazard with potentially avoidable health damages—yet communities' abilities to avoid these damages may diverge. The size of the US-wildfire problem is considerable: between 2018–2021, wildfires cost more than $62 billion[30]. In the same years, *every* Census Block Group (CBG) on the West Coast faced wildfire smoke during at least 14 weeks (Figure 1). As wildfires ravaged larger and larger swaths of the US[31–37]—potentially unraveling decades of improved air quality[38]—individuals increasingly confronted the choice to face fires' smoke or flee.

Existing work documents the considerable health consequences of wildfire-smoke exposure (mortality, morbidity, and adverse birth outcomes)—and the particulate matter ($PM_{2.5}$) associated[2,35] with the wildfire smoke[39–47]. Temporary relocation can avoid smoke altogether—reducing smoke-related health costs. However, temporary and unexpected relocation may only be feasible for some (likely more-privileged) households. This inequality in individuals' abilities to relocate may generate unequal damages from smoke exposure—exacerbating existing inequality.

We estimate the effect of wildfire smoke on short-term out-migration and how this smoke-induced migration varies by communities' racial, ethnic, or income compositions—testing whether communities equally apply avoidance strategies. For this analysis, we combine remotely sensed smoke plumes, cellphone-based movement data, and CBG-level demographic data for all recorded wildfire smoke in the US's West Coast during 2018–2021. Our results show that, on average, individuals temporarily relocate when they face wildfire smoke. Residents travel farther and are more likely to leave their home counties when facing smoke at home.

However, these first results hide substantial heterogeneity. We find that historically marginalized

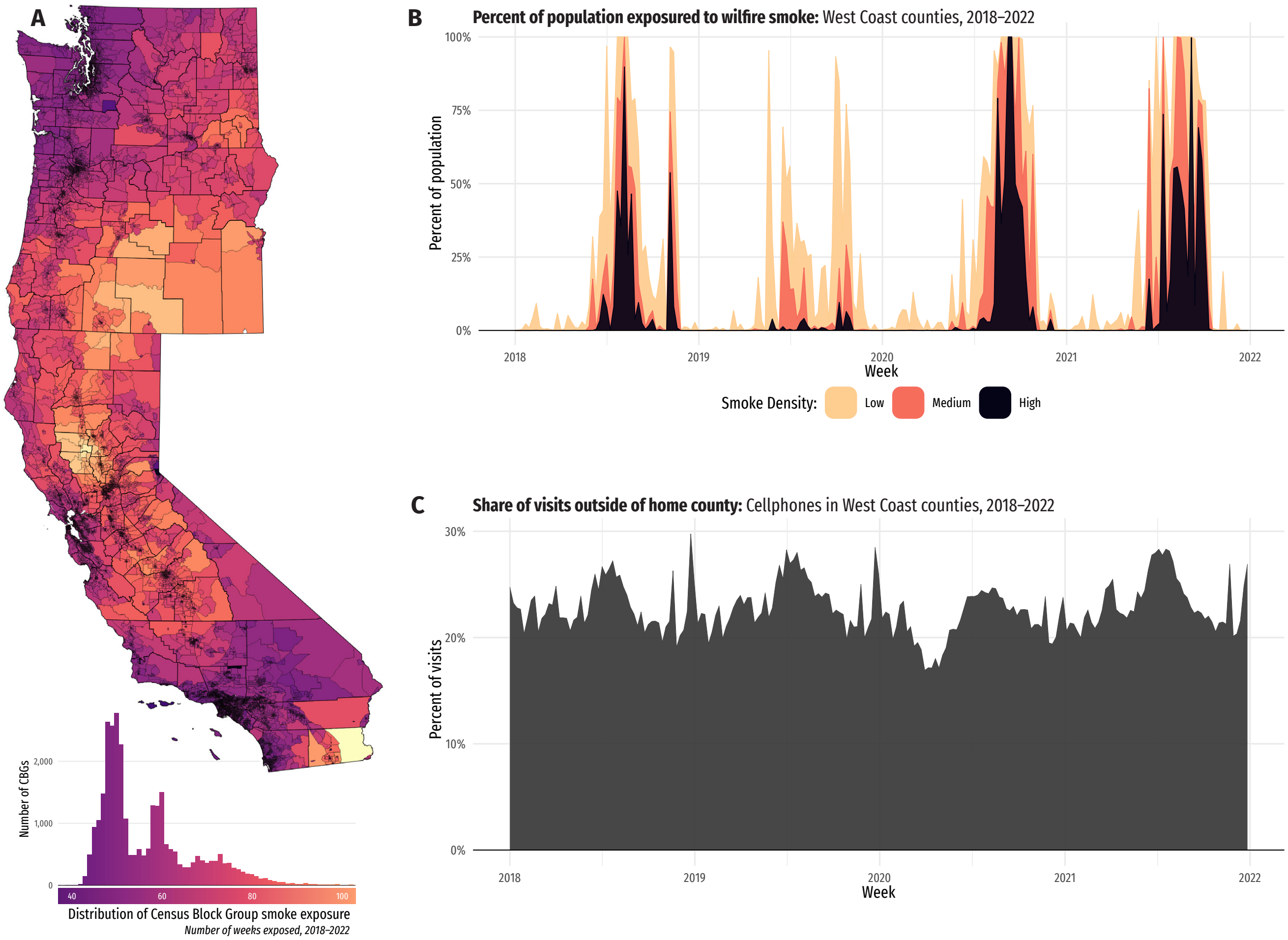


Figure 1. Spatiotemporal smoke exposure and mobility. A illustrates the study area—the West Coast of the United States. The smallest features in the map in **A** are shaded in proportion to the number of weeks the Census Block Groups (CBGs) experienced any wildfire smoke 2018–2021. **B** depicts the share of the Western US population exposed to three smoke densities by week. **C** shows each week's share of cellphone-based movement that occurred outside of individuals' home counties.

populations—Black, Hispanic, and low-income communities—are significantly less likely to out-migrate when facing the same wildfire smoke as more privileged populations. This heterogeneity mirrors other inequality in individuals' travel habits when smoke is absent—and many already-documented inequalities. Together, these results illustrate fundamental inequities in abilities to respond to major risks/damages and suggest potentially fruitful avenues for policy.

Background and motivation Our results contribute to three strands in the literature: environmental justice/inequality, defensive investments and avoidance/adaptation, and human responses to wildfires.

First, our results offer new insights into the burdens facing lower-income, Black, and Hispanic communities. A large environmental justice (EJ) and inequality literature documents numerous dimensions along which historically marginalized communities face worse environmental quality—*e.g.*, in exposure to toxic-release facilities[15,16], air pollution[17–19], and noise[48]. Much of this literature focuses on unequal exposure to environmental hazards. Our findings complement this EJ thread by showing even when external (outdoor) exposure is 'equitable'—wildfire smoke covers large areas—adaptation/defensive responses can be unequal. In particular, we show that when wildfire smoke covers an area, historically disadvantaged communities *in that area* are less likely to out-migrate relative to more affluent and more White communities.

We also contribute to a growing literature that measures avoidance behaviors and defensive investments employed against environmental risks. Avoidance strategies in this literature include consumption choices, (*e.g.*, purchases of water bottles[49], pharmaceuticals[50], masks[51,52], and air purifiers[53]) structural investments[54], long-term migration[55–62], and short-term travel[2,39,63–65]. Short-term travel and equity have received less attention—likely due to historical data limitations. Recent work shows younger, more-educated individuals are more likely to permanently migrate due to pollution[62], and more affluent individuals are more likely to make defensive investments—masks[51]. Our (short-run) migration results also relate to the climate-adaption literature[66–73]. Our results help fill this gap—estimating the extent of short-term out-migration and its distribution across socioeconomic groups. Previous work has suggested that costs related to avoidance activities and defensive investments are on the same scale as the health costs of exposure—*i.e.*, the health costs mitigated by avoidance may be quite large[50,74]. Consequently, if avoidance strategies are mainly available to (or employed by) more-advantaged communities, less-advantaged communities may bear substantial and disproportionate shares of the health burden of exposure. Our results suggest that this concern is legitimate.

Finally, we contribute to the literature on the social and economic effects of wildfires. Recent work in this space raises equity concerns in the allocation of fire-fighting resources[75–77], the incidence of wildfire hazard[78], the incidence of fire suppression costs[34], and the burden of wildfire smoke[79]. Limited previous work exists on avoidance behaviors in the setting of wildfires. One exception[39] provides survey-based evidence of averting actions from sample respondents after the 2009 Station Fire in Los Angeles County, California. Our results merge these two branches of the wildfire literature—equity and avoidance.

Our results on wildfire-smoke avoidance behavior are most similar to recent work by Burke *et al.* who show that individuals are aware of smoke exposure (via Google searches), seek protection (*e.g.*, "air purifier" searches), are more likely to remain at home for the entire day when facing smoke-generated $PM_{2.5}$—with more affluent households more likely to remain home[2]. This last result highlights a complementary avoidance strategy to the behavior that we investigate, which the authors also find is accessed unequally. Our exposure variables also differ from Burke *et al.*: we focus on all 'wildfire smoke' rather than $PM_{2.5}$. While $PM_{2.5}$ represents a major concern for public health, our goal in this paper is to estimate the behavioral effects of wildfire smoke *itself*—rather than hazardous particulates caused by smoke.

Empirical approach To estimate the impact of wildfire smoke on temporary out-migration, we merge satellite-derived data on wildfire smoke plumes with cellphone-based movement data and CBG demographics. The resulting dataset represents a CBG by week-of-sample panel. We then employ a two-way fixed effects (TWFE) estimator—regressing communities' out-migration on their smoke exposures, with fixed effects for CBG and for week of sample. This estimator essentially compares smoke-affected communities to unaffected communities within the same week of sample, after removing cross-sectional differences across communities and temporal differences/trends through time. Finally, we flexibly estimate heterogeneity in communities' tendencies to out-migrate when facing wildfire smoke using a semi-parametric specification that interacts the smoke-exposure indicator with indicators based upon CBGs' demographics—estimating separate coefficients for different groups.

The main exposure/treatment of interest in this paper is wildfire smoke. We define a CBG as exposed to wildfire smoke in a week if the CBG's boundaries overlap with any smoke plumes from NOAA's Hazard Mapping System Fire and Smoke Product[80] during that week.[1] Figure 1A maps the cross-sectional variability in this smoke-exposure measure. From 2018–2021, West Coast CBGs faced considerable smoke exposure—every CBG encountered smoke in at least 40 weeks—and this exposure varied greatly, spanning 40–100 weeks. Figure 1B depicts the substantial temporal variation in these CBGs' smoke exposure—ranging from 0% to 100% of the population exposed in a week.

Our main outcomes relate to individuals' decisions to temporary relocate. If temporary relocation spikes in smoke-covered weeks, then we have evidence of temporary relocation as a smoke-avoidance strategy. If this relocation behavior varies by individuals' demographics, then we have evidence of unequal access or application of this avoidance strategy.

We use cellphone-based movement data from SafeGraph's *Weekly Patterns* dataset[81] to measure such temporary out-migration. This dataset records location 'visits' (restaurants, grocery stores, *etc.*) from 45 million cellphones, aggregated to cellphones' home CBG. If individuals travel away from smoke, then the number of out-of-county visits should increase relative to the number of total visits. Accordingly, our first

[1] Section A.1 elaborates on these and other data sources.

measure of out-migration is the percentage of a CBG's visits that occurred outside of the CBG's county (calculated for each week). Our second measure is the 75th percentile of distances traveled by the CBG's phones in a given week—providing information on how the right tail of distance-traveled distribution changes due to wildfire smoke. Figure 1C illustrates the temporal variation in the share of visits that occur out-of-county, ranging 18–30%. Notably, peaks in out-migration appear to coincide with peak smoke-exposure moments. We turn to a regression model test this visual relationship.

Finally, we use CBGs' demographics in the American Community Survey (ACS) to estimate how communities' responses to smoke vary by their racial, ethnic, and income compositions[82]. From these demographic measures (income; population shares Black, Hispanic, White) we construct percentiles (0–100) as percentiles smooth skewed distributions. Our regression model uses indicators based upon two-percentile bins (*e.g.*, an indicator for the 49th and 50th percentiles) to flexibly estimate heterogeneity with respect to demographics—testing whether smoke avoidance is more common or more intense within specific demographic groups.

The combination of spatial disaggregation to CBG and temporal aggregation to week allow us to contribute to this literature's understanding of smoke-induced out-migration—finding significant evidence that income, race, and ethnicity correlate with CBGs' tendencies to out-migrate.

Results

Population-wide response to smoke We first estimate the average response to wildfire smoke exposure without considering heterogeneity, pooling potentially heterogeneous responses across all urban CBGs on the West Coast.[2]

Column (1) of Table 1 demonstrates that, on average, communities significantly increase out-migration when they face wildfire smoke. The two panels of the table separate results for the two dependent variables. In Panel A, the dependent variable is the percentage (0–100) of POI visits from a CBG's residents that occur outside the CBG's county. Panel B's outcome is the 75th percentile of distance traveled to POIs. Each column in each panel results from a separate regression with the same fixed-effect specification—CBG and week-of-sample.[3] The standard-error estimator allows clustering within county and month-of-year (*e.g.*, January).

In Column (1) of Panel A (Table 1), we estimate that smoke significantly increases a CBG's share of

[2] *I.e.*, Equation 1 without interacting smoke exposure with percentile.

[3] Table S3 reproduces the estimates in Table 1 but uses state by week-of-sample fixed effects. Table S4 drops CBGs affected by wildfires between 2018-2021. Results across the three tables are very similar.

	(1)	(2)	(3)	(4)	(5)
		Percentile-based heterogeneity			
		HH Income	% Black	% Hispanic	% White
Panel A *Dependent variable: Percent of visits outside of home county*					
Any smoke	0.28**	−0.41	0.54***	0.89**	−0.10
	(0.10)	(0.30)	(0.15)	(0.39)	(0.21)
Any smoke × Het. percentile		1.4**	−0.49*	−1.2	0.80*
		(0.53)	(0.24)	(0.70)	(0.38)
N obs. (millions)	5.63	5.63	5.63	5.63	5.63
Panel B *Dependent variable: 75th percentile of distance traveled (km)*					
Any smoke	1.7**	−6.9	6.0***	11.5*	−3.4
	(0.55)	(4.0)	(1.9)	(5.9)	(2.3)
Any smoke × Het. percentile		17.2**	−8.1*	−18.8	10.7*
		(7.6)	(3.7)	(11.4)	(4.9)
N obs. (millions)	5.63	5.63	5.63	5.63	5.63
Fixed effects					
CBG	✓	✓	✓	✓	✓
Week of sample	✓	✓	✓	✓	✓

Table 1. Wildfire smoke increases short-term out-migration—particularly in more affluent, less Black, less Hispanic, and more White CBGs. Each panel-by-column represents separate regression results. **Panel A** estimates the effect of smoke exposure on the percent (0–100) of POI (SafeGraph place of interest) visits that occur within visitors' home counties; **Panel B** estimates the effect of smoke exposure on the 75th percentile of distance traveled to POIs. Columns (2–5) estimate heterogeneity by CBGs' percentile (0–1) of household income, % Black, % Hispanic, and % White. Each column in each panel represents a separate regression—using the same fixed-effect specification of CBG and week-of-sample. Observations are weighted by CBG population. Table S3 reproduces the current table with *state by week-of-sample* fixed effects; Table S4 replicates the table after dropping CBGs directly affected by wildfires. Standard errors allow clustering within county and month-of-year (*e.g.*, January). Significance codes: ***: 0.01, **: 0.05, *: 0.1.

out-of-county POI visits by 0.28 percentage points. On average, approximately 22% of POI visits occur outside of residents' home counties (Table S1, Panel B). Thus, this smoke-induced increase in out-migration represents a 1.3-percent increase relative to the sample-average out-migration rate. This result suggests a small—yet significant—subset of the population of *all West Coast CBGs* consistently travels away from their home counties when smoke plumes cover their homes. In the next section, we ask whether this behavior correlates with CBGs' socioeconomic compositions.

Column (1) of Panel B also documents statistically significant evidence of smoke-induced out-migration—specifically, the 75$^{\text{th}}$ percentile of a CBG's distance traveled significantly increases when CBGs face smoke. We estimate that the 75$^{\text{th}}$ percentile increases by 1.7 kilometers when smoke plumes intersect with the CBG. This 1.7-kilometer increase is relative to a sample average of 48.4 kilometers (Table S1, Panel B), implying a sizable (3.5-percent) increase in the 75$^{\text{th}}$ percentile of travel in weeks with smoke. Put differently: wildfire smoke pulls out the right tail of the distance-traveled distribution for urban, west-coast CBGs.

Both panels of Table 1 offer statistically significant evidence that out-migration increases when communities face wildfire smoke. However, these estimators pool behavior across heterogeneous communities—potentially missing important differences in individuals' responses to wildfire smoke exposure. The following sections examine how out-migration behavior correlates with income, race, and ethnicity.

Income and smoke migration We now turn to the results of income-based heterogeneity in smoke-induced out-migration. Column (2) of Table 1 repeats the regressions of the previous section but allows heterogeneity by CBGs' income.[4]

Both outcomes (panels) in Table 1 reveal sizable and statistically significant relationships between communities' smoke-based out-migration behavior and income. The heterogeneity's direction follows a pattern common in the environmental- and social-justice literatures: more privileged communities display heightened avoidance behavior—here, out-migration—in the presence of wildfire smoke. Among the lowest-income communities, there is no statistically significant evidence of out-migration. The level of out-migration only differs significantly from zero for communities above the 47$^{\text{th}}$ percentile of income for out-of-county travel (Panel A) and the 49$^{\text{th}}$ percentile for distance traveled (Panel B).

More-affluent communities out-migrate substantially—and significantly—more than lower-income communities. The interaction coefficients in Column (2) indicate that smoke increases the share of other-

[4]We estimate Equation 1 with Percentile_i defined as CBG i's percentile (between 0 and 1) in the West Coast's median-household income distribution. *E.g.*, a CBG with median household income of $74,000 is in the 50$^{\text{th}}$ percentile and would have $\text{Percentile}_i = 0.50$.

county visits for the top income percentile by 1.4 percentage points and increases their 75$^{\text{th}}$ percentile of travel by 17.2 kilometers. The effects for the most-affluent communities are 3–6 times larger than the pooled effects presented in Column (1).

Table 1 provides strong evidence that affluent communities travel to avoid smoke, while there is no significant evidence low-income communities access this strategy.

The empirical specification in Table 1 imposes linearity in the relationship between CBGs' income percentiles and heterogeneous smoke-induced out-migration. We relax this restriction by specifying *Percentile* as 50 mutually exclusive indicator variables (*i.e.*, two-percentile bins, *e.g.*, an indicator for communities in the the 49$^{\text{th}}$–50$^{\text{th}}$ percentiles).[5] These indicators allow substantial flexibility in modeling potential heterogeneity in communities' out-migration behavior.

Panel A of Figure 2 illustrates the results of this semi-parametric specification for income-based heterogeneity. Subfigure i illustrates how communities' tendencies to out-migrate due to smoke correlates with their incomes—providing point estimates and 95% confidence intervals for each of the 50 income-percentile bins. Subfigure ii depicts income bins' general tendencies to travel beyond their home counties, throughout the year, regardless of smoke. Finally, Subfigure iii depicts each bins' median income.[6]

The results from this semi-parametric specification corroborate those of the simpler regression in Table 1: a community's tendency to out-migrate away from smoke strongly correlates with its income. Communities with income below the 50$^{\text{th}}$ percentile do not, on average, significantly out-migrate when facing smoke; most estimates are quite close to zero and do not statistically reject zero. On the other hand, communities above the 50$^{\text{th}}$ percentile generally show statistically significant evidence of out-migration away from smoke; the magnitude of out-migration grows with communities' income. While the increase in out-migration appears quite linear in communities' income percentile (the horizontal axis), out-migrate appears to sharply increase above the 90$^{\text{th}}$ percentile—approximately the same point at which the income distribution sharply increases. The estimates from this semi-parametric estimation (depicted Figure 2Ai) suggest an even higher rate of smoke-induced out-migration ($\sim$1.4 percent) relative to the results from the linear-specification results in Table 1.[7]

Subfigure 2Aii demonstrates income strongly (and positively) correlates with communities' out-of-county travel throughout the year, regardless of smoke. The same communities that are more likely to

[5] We also drop the main effect (Smoke_{iw} in Equation 1)—rather than dropping one of the individual indicator variables—so that we can directly compare percentiles' tendencies to out-migrate.

[6] Figure S2A reproduces Figure 2A with distance traveled as the outcome.

[7] These insights are also consistent with our distance-traveled measure (Figure S2).

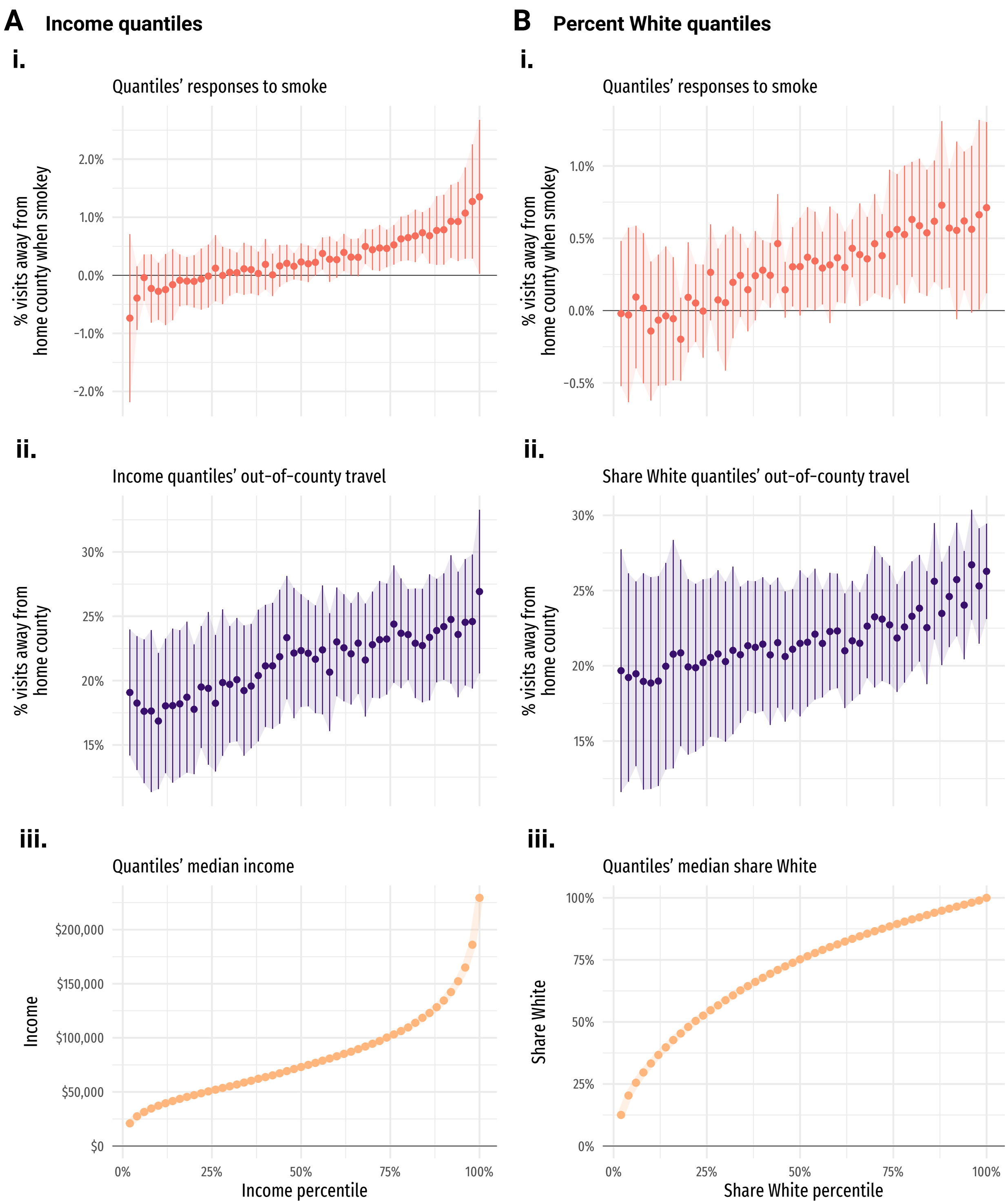


Figure 2. More affluent and more White communities are more likely to out-migrate in the presence of smoke. Panels A and B report percentile-based results by CBGs' median income or population-share White (respectively). The horizontal axis provides the percentile throughout the figure. Within each panel: Subfigure i depicts point estimates and 95% confidence intervals of smoke-induced out-migration for each percentile bin. Subfigure ii reports 'baseline' propensity to travel outside their home county, regardless of smoke exposure. Subfigure iii illustrates how percentiles map into variable's value (income or share White).

out-migrate in the presence of smoke are already traveling more.

Both specifications of income-based heterogeneity—and both measures of out-migration—produce the same conclusion: In the presence of wildfire smoke, wealthier communities are significantly more likely to out-migrate than poorer communities. Further, there is no significant evidence that smoke induces any out-migration in communities below the 30$^{\text{th}}$ percentile of income.

Race, ethnicity, and smoke migration Disparities in smoke-induced out-migration extend to race and ethnicity. Columns 3–5 of Table 1 estimate heterogeneity in smoke-induced out-migration as a function of CBGs' racial- or ethnic-composition percentiles. Similar to the preceding income-based heterogeneity analysis, we now examine how smoke-induced out-migration varies across communities by their position (percentile, from 0 to 1) in the West Coast distribution of racial/ethnic composition: population share Black (Column 3), Hispanic (Column 4), or White (Column 5).[8]

Table 1 further substantiates historical privilege[9] correlates with communities' tendencies to out-migrate when facing wildfire smoke. Column (3) estimates that smoke significantly increases the share of out-of-county travel in the West Coast's least-Black communities by 0.54 percentage points and increases their distance traveled by 6 kilometers. However, the most-Black communities show no significant evidence of smoke-induced out-migration: neither out-of-county travel nor distance traveled. Communities that are at least five percent Black (above 65$^{\text{th}}$ percentile in the West Coast's distribution) show no significant evidence of smoke-base out-migration (*i.e.*, confidence intervals include zero).

The story is similar in Hispanic communities: Column (4) documents that the least-Hispanic communities significantly respond to smoke in their share of out-of-county trips (increasing by 0.89 percentage points) and in the distance traveled (increasing the 75$^{\text{th}}$ percentile by 11.5 kilometers). As with the most-Black communities, the most-Hispanic communities show no significant evidence of smoke-induced out-migration. Communities whose population is at least 24-percent Hispanic (above the 54$^{\text{th}}$ percentile) show no significant evidence of smoke-based out-migration.

Column (5) of Table 1 also bears evidence of disparities in out-migration that correlate with privilege: urban communities with larger White population shares out-migrate more than less-White communities. The least-White communities ($<$25% White) show no statistically significant evidence of out-migration in terms of out-of-county travel or distance traveled—both estimates are negative and do not differ significantly from zero. When facing wildfire smoke, the most-White urban communities ($\sim$100% White)

[8] *E.g.*, , a CBG with 5-percent Black population sits at the 65$^{\text{th}}$ percentile of the West Coast distribution.
[9] *I.e.*, populations that are less Black, less Hispanic, and/or more White.

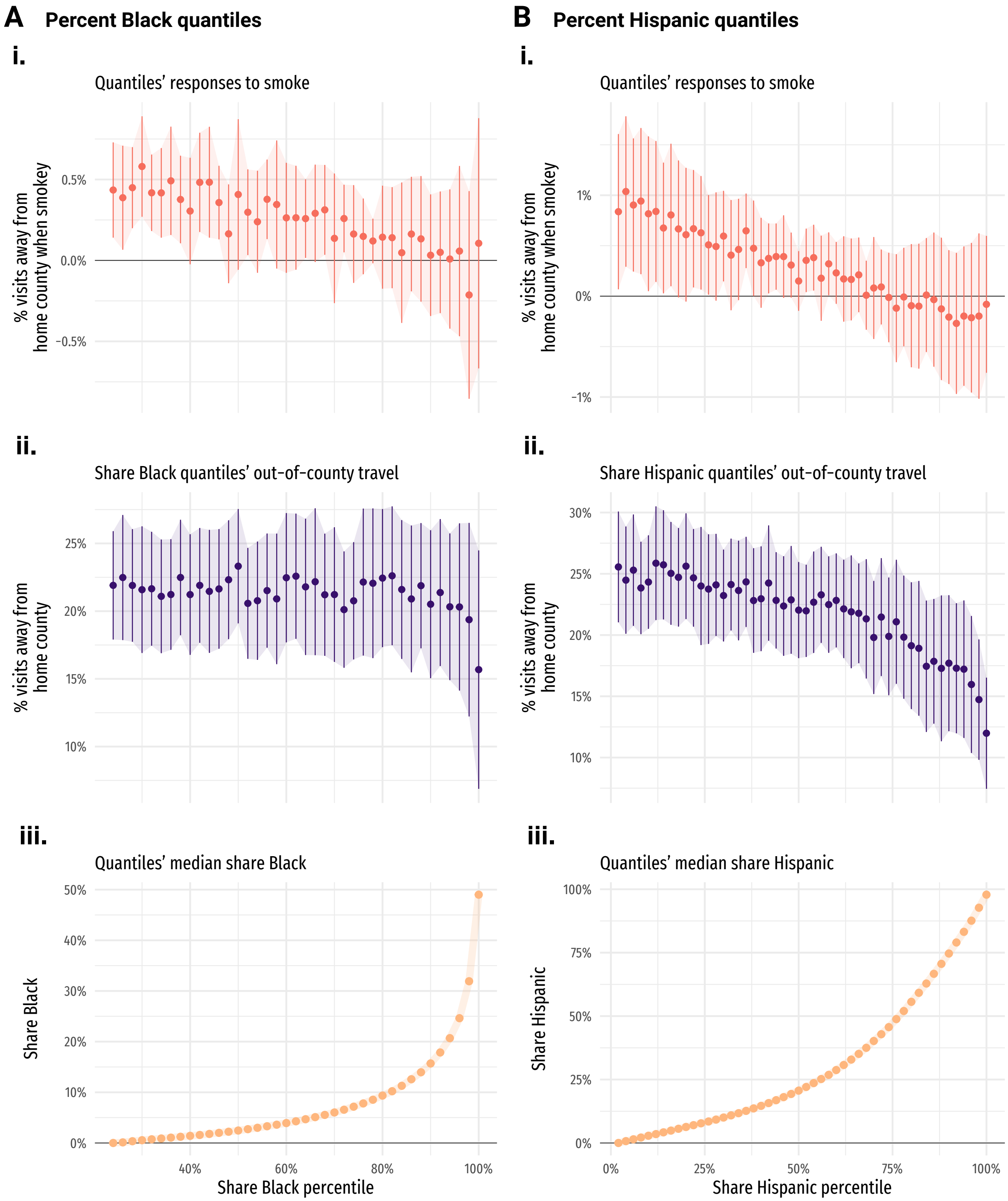


Figure 3. Black and Hispanic communities are less likely to out-migrate in the presence of smoke. This figure follows the same layout as Figure 2 but instead focuses on communities' population share Black (Panel A) or Hispanic (Panel B). The horizontal axis provides the percentile throughout the figure. Within each panel: Subfigure i depicts point estimates and 95% confidence intervals of smoke-induced out-migration for each percentile bin. Subfigure ii reports 'baseline' propensity to travel outside their home county, regardless of smoke exposure. Subfigure iii illustrates how percentiles map into variable's value (income or share White).

out-migrate significantly more than less-White communities. Communities above the 41st percentile of share White (communities that are at least 69% White) show statistically significant evidence of smoke-induced out-migration.

To examine potential nonlinearities, we now turn to our semi-parametric approach—incorporating indicator variables for communities' racial/ethnic-composition percentiles to flexibly capture heterogeneity in out-migration responses. Panels A and B of Figure 3 present results for the shares of Black and Hispanic residents, respectively; Panel B in Figure 2 depicts the corresponding results for the share of White residents.[10]

The semi-parametric specification reinforces that out-migration is strongly correlated with communities' racial and ethnic composition: migration responses are higher in less-Black, less-Hispanic, and more-White areas. At roughly the point in the distribution where communities become majority White (the 25th percentile; see Figure 2Biii), we observe a sharp increase in smoke-induced out-migration. Majority-non-White communities, by contrast, exhibit little to no smoke-related out-migration: point estimates remain close to zero and fail to reject it. Among majority-White CBGs, the magnitude of smoke-induced out-migration rises with the share of White residents.

Conversely, when the share of Hispanic residents in a CBG crosses 50% (*i.e.*, becomes majority-Hispanic, $\sim$75th percentile; see Panel 3Biii), out-migration is near zero and becomes slightly negative as the share Hispanic increases. Very few CBGs on the West Coast are majority Black—roughly 80% of urban West Coast CBGs have populations that are less than 10% Black. Nevertheless, Panel 3A reveals a clear pattern: communities with larger Black-population shares migrate substantially less in response to smoke relative to less-Black communities.

In addition to the significant disparities in smoke-induced out-migration that we discuss above, the middle subfigures (labeled *ii*) of Figures 2 and 3 depict striking differences in general (non-smoke-related) travel patterns. As communities become more Black, more Hispanic, less White, or less affluent, their out-of-county travel declines. The trend in communities' Hispanic population is particularly notable in its magnitude and nonlinearity: only 12% of POI visits occur outside individual's home counties in the most-Hispanic communities, whereas 25% visits are out-of-county least-Hispanic communities.

[10] Figure S3 replicates these figures using the 75th percentile of distance traveled.

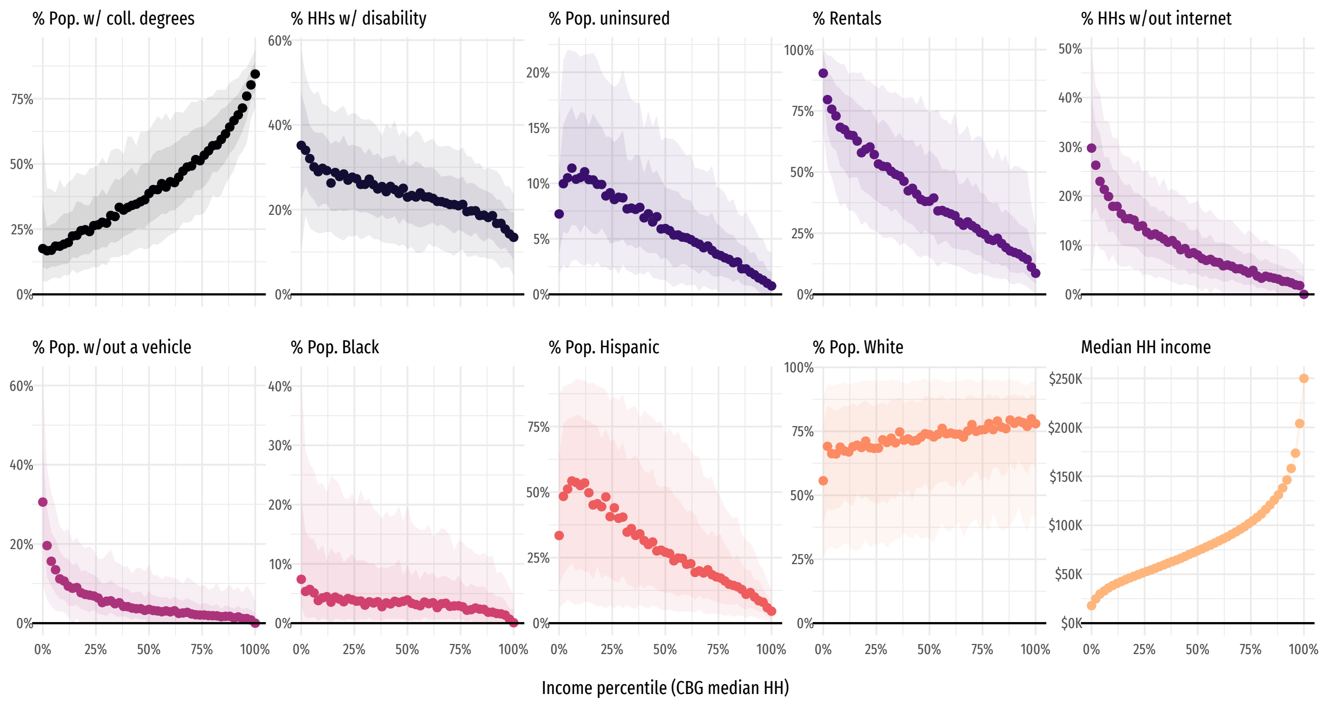


Figure 4. Urban CBG income percentile maps into many potential mechanisms among other socioeconomic dimensions. Each subfigure summarizes urban, west-coast CBGs levels of the given variable by two-percentile bins (*e.g.*, combining the first and second percentiles). Solid dots the median. The first, darker band gives the interquartile range (25^{th}–75^{th} percentiles) for the given bin. The lighter band marks the 10^{th}–90^{th} percentiles. Note that vertical axis scales change across subfigures to match variables' differing variation. Color denotes different variables.

Discussion

This study provides two main findings: (1) some households temporarily relocate in response to wildfire smoke, and (2) this behavioral response is strongly correlated with socioeconomic privilege. While prior work has documented that households (unequally) stay in place when facing smoke, we provide the first (to our knowledge) evidence of this complementary avoidance strategy and its inequitable distribution.

Notably, the dimensions along which we document heterogeneous out-migration are descriptive (*i.e.*, non-causal). While our empirical strategy provides plausibly exogenous variation in smoke exposure, it does not provide identifying variation in income, race, or ethnicity. However, showing inequality in avoidance correlates with contemporary and historical privilege is critical for social equity, public policy, and future research.

Figure 4 documents how one of our dimensions—income percentile—correlates with nine socioeconomic variables from the ACS (for urban, West-Coast CBGs). Solid dots denote variables' medians for the given income-percentile bin. Darker shading denotes bins' interquartile range (25^{th}–75^{th} percentiles); lighter shading shows bins' 10^{th}–90^{th} percentiles.

Across many dimensions, Figure 4 illustrates how strongly income correlates with variables critical to equity, policy, and potential mechanisms behind out-migration. Income, race, and ethnicity all map into differences in education, employment, information, and transportation access. Accordingly, the differences in out-migration that we document should not be interpreted as being *caused* by race, ethnicity, or even income. Instead, they likely reflect latent disparities—historical, structural, and others—that shape households' ability to travel to avoid smoke exposure and may, in turn, generate or exacerbate inequities in smoke and particulate-matter exposures/damages.

Regarding social equity: Our results demonstrate yet another dimension multiplying inequity in disadvantaged communities. Communities less likely to travel away from smoke are also more likely to inhabit homes easily penetrated by smoke and pollution (*e.g.*, rentals and mobile homes), live in polluted areas, face significant health issues, and lack health insurance. In other words, communities that are more likely to stay home amidst smoke are likely facing more smoke *inside* their homes and starting with worse health. Together, these factors may explain why poorer and historically marginalized communities appear to be more susceptible to smoke exposure[79,83]. This situation compounds inequality.

Compounding disadvantages may suggest high-return areas for policy. For example, policies that improve houses' *seals* (*i.e.*, weatherization and energy efficiency programs that prevent outside smoke and pollution from entering the home) may be especially beneficial in communities less able/likely to travel away from smoke. The environmental-justice literature demonstrates that these households are also more likely to inhabit more polluted areas[18] and face serious health challenges (*e.g.*, higher rates of disability, as in Figure 4). Beyond avoiding smoke exposure, improved seals could also reduce the burden caused by unequal outdoor-pollution exposure. Such improvements would likely improve these homes' energy efficiency, reducing these households' utility bills. Additional research can better direct such policies.

Finally, our results highlight additional fruitful topics for future research—especially in understanding the mechanisms that cause unequal levels of out-migration across income, race, and ethnicity. Wealth is one obvious possible mechanism. Differing job types (*e.g.*, hourly vs. salaried) or job benefits (income and college degrees correlate strongly in Figure 4) may also explain unequal avoidance; unplanned travel requires a degree of professional flexibility. Access to transportation offers another possible mechanism: Figure 4 shows that low-income households are substantially less likely to have access to a vehicle. Information may also play a role—particularly for subscription-based sources like internet and newspapers. Of course, there are many other potential mechanisms—*e.g.*, liquidity or credit access. Future research can pursue these paths.

Although populations may face common hazards, individuals and communities do not equally employ avoidance strategies. We find robust and significant evidence that *some* communities relocate in response to wildfire smoke, whereas others show little evidence of out-migration. These disparities align closely with income, race, and ethnicity—dimensions tied to contemporary and historical disadvantage. Without targeted policies or interventions, unequal access to avoidance may compound existing inequities, amplifying the disparate burdens of wildfire smoke and other climate-related hazards in the decades ahead.

References

1. IPCC. *Global Warming of 1.5°C* (Cambridge University Press, 2022).
2. Burke, M. *et al.* Exposures and behavioural responses to wildfire smoke. *Nat. Hum. Behav.* DOI: 10.1038/s41562-022-01396-6 (2022).
3. Harper, S., Lynch, J., Burris, S. & Smith, G. D. Trends in the black-white life expectancy gap in the united states, 1983-2003. *JAMA* **297**, 1224, DOI: 10.1001/jama.297.11.1224 (2007).
4. Chetty, R. *et al.* The association between income and life expectancy in the united states, 2001-2014. *JAMA* **315**, 1750, DOI: 10.1001/jama.2016.4226 (2016).
5. Currie, J. & Schwandt, H. Mortality inequality: The good news from a county-level approach. *J. Econ. Perspectives* **30**, 29–52, DOI: 10.1257/jep.30.2.29 (2016).
6. Currie, J. & Schwandt, H. Inequality in mortality decreased among the young while increasing for older adults, 1990–2010. *Science* **352**, 708–712, DOI: 10.1126/science.aaf1437 (2016).
7. Alsan, M., Chandra, A. & Simon, K. The great unequalizer: Initial health effects of COVID-19 in the united states. *J. Econ. Perspectives* **35**, 25–46, DOI: 10.1257/jep.35.3.25 (2021).
8. Schwandt, H. *et al.* Inequality in mortality between black and white americans by age, place, and cause and in comparison to europe, 1990 to 2018. *Proc. Natl. Acad. Sci.* **118**, DOI: 10.1073/pnas.2104684118 (2021).
9. Currie, J. Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *J. Econ. Lit.* **47**, 87–122, DOI: 10.1257/jel.47.1.87 (2009).
10. Almond, D. & Chay, K. Y. The long-run and intergenerational impact of poor infant health: Evidence from cohorts born during the civil rights era. *Work. Pap.* (2006).
11. Aizer, A. & Currie, J. The intergenerational transmission of inequality: Maternal disadvantage and health at birth. *Science* **344**, 856–861, DOI: 10.1126/science.1251872 (2014).
12. Chandra, A., Kakani, P. & Sacarny, A. Hospital allocation and racial disparities in health care. *NBER Work. Pap. 28018* DOI: 10.3386/w28018 (2020).
13. Dieleman, J. L. *et al.* US health care spending by race and ethnicity, 2002-2016. *JAMA* **326**, 649, DOI: 10.1001/jama.2021.9937 (2021).
14. Singh, M. & Venkataramani, A. Capacity strain and racial disparities in hospital mortality. *NBER Work. Pap. 30380* DOI: 10.3386/w30380 (2022).
15. Mohai, P. & Saha, R. Racial inequality in the distribution of hazardous waste: A national-level reassessment. *Soc. Probl.* **54**, 343–370 (2007).
16. Bullard, R. D., Mohai, P., Saha, R. & Wright, B. Toxic wastes and race at twenty: Why race still matters after all of these years. *Envtl. L.* **38**, 371 (2008).
17. Hsiang, S., Oliva, P. & Walker, R. The distribution of environmental damages. *Rev. Environ. Econ. Policy* **13**, 83–103, DOI: 10.1093/reep/rey024 (2019).
18. Colmer, J., Hardman, I., Shimshack, J. & Voorheis, J. Disparities in $PM_{2.5}$ air pollution in the united states. *Science* **369**, 575–578, DOI: 10.1126/science.aaz9353 (2020).
19. Clark, L. P., Harris, M. H., Apte, J. S. & Marshall, J. D. National and intraurban air pollution exposure disparity estimates in the united states: Impact of data-aggregation spatial scale. *Environ. Sci. & Technol. Lett.* **9**, 786–791, DOI: 10.1021/acs.estlett.2c00403 (2022).
20. Bertocchi, G. & Dimico, A. The racial gap in education and the legacy of slavery. *J. Comp. Econ.* **40**, 581–595, DOI: 10.1016/j.jce.2012.04.001 (2012).

21. Autor, D., Figlio, D., Karbownik, K., Roth, J. & Wasserman, M. Family disadvantage and the gender gap in behavioral and educational outcomes. *Am. Econ. Journal: Appl. Econ.* **11**, 338–381, DOI: 10.1257/app.20170571 (2019).

22. Elder, T. E., Figlio, D. N., Imberman, S. A. & Persico, C. L. School segregation and racial gaps in special education identification. *J. Labor Econ.* **39**, S151–S197, DOI: 10.1086/711421 (2021).

23. Blanden, J., Doepke, M. & Stuhler, J. Educational inequality. *NBER Work. Pap. 29979* DOI: 10.3386/w29979 (2022).

24. Chung, C., Myers, S. L. & Saunders, L. Racial differences in transportation access to employment in chicago and los angeles, 1980 and 1990. *Am. Econ. Rev.* **91**, 174–177, DOI: 10.1257/aer.91.2.174 (2001).

25. Chetty, R., Hendren, N., Kline, P. & Saez, E. Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Q. J. Econ.* **129**, 1553–1623, DOI: 10.1093/qje/qju022 (2014).

26. Chetty, R., Hendren, N., Lin, F., Majerovitz, J. & Scuderi, B. Childhood environment and gender gaps in adulthood. *Am. Econ. Rev.* **106**, 282–288, DOI: 10.1257/aer.p20161073 (2016).

27. Aneja, A. & Xu, G. The costs of employment segregation: Evidence from the federal government under woodrow wilson. *The Q. J. Econ.* **137**, 911–958, DOI: 10.1093/qje/qjab040 (2021).

28. Aneja, A. & Avenancio-Leon, C. F. The effect of political power on labor market inequality: Evidence from the 1965 voting rights act. *Am. Econ. Rev.* **Forthcoming** (2022).

29. Davis, J. M. V. & Mazumder, B. The decline in intergenerational mobility after 1980. *Fed. Reserv. Bank Chic. Work. Pap. 2014-28* DOI: 10.2139/ssrn.3138979 (2022).

30. Smith, A. B. U.s. billion-dollar weather and climate disasters, DOI: 10.25921/STKW-7W73 (2022).

31. Radeloff, V. C. *et al.* The wildland-uban interface in the united states. *Ecol. Appl.* **15**, 799–805, DOI: 10.1890/04-1413 (2005).

32. Westerling, A. L., Hidalgo, H. G., Cayan, D. R. & Swetnam, T. W. Warming and earlier spring increase western u.s. forest wildfire activity. *Science* **313**, 940–943, DOI: 10.1126/science.1128834 (2006).

33. Radeloff, V. C. *et al.* Rapid growth of the US wildland-urban interface raises wildfire risk. *Proc. Natl. Acad. Sci.* **115**, 3314–3319, DOI: 10.1073/pnas.1718850115 (2018).

34. Baylis, P. & Boomhower, J. The economic incidence of wildfire suppression in the united states. *Am. Econ. Journal: Appl. Econ.* **Forthcoming** (2022).

35. O'Dell, K., Ford, B., Fischer, E. V. & Pierce, J. R. Contribution of wildland-fire smoke to US $PM_{2.5}$ and its influence on recent trends. *Environ. Sci. & Technol.* **53**, 1797–1804, DOI: 10.1021/acs.est.8b05430 (2019).

36. Burke, M. *et al.* The changing risk and burden of wildfire in the united states. *Proc. Natl. Acad. Sci.* **118**, DOI: 10.1073/pnas.2011048118 (2021).

37. Goss, M. *et al.* Climate change is increasing the likelihood of extreme autumn wildfire conditions across california. *Environ. Res. Lett.* **15**, 094016, DOI: 10.1088/1748-9326/ab83a7 (2020).

38. Burke, M. *et al.* The contribution of wildfire to pm2.5 trends in the usa. *Nature* **622**, 761–766, DOI: 10.1038/s41586-023-06522-6 (2023).

39. Richardson, L. A., Champ, P. A. & Loomis, J. B. The hidden cost of wildfires: Economic valuation of health effects of wildfire smoke exposure in southern california. *J. For. Econ.* **18**, 14–35, DOI: 10.1016/j.jfe.2011.05.002 (2012).

40. Liu, J. C. *et al.* Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties. *Epidemiology* **28**, 77–85, DOI: 10.1097/ede.0000000000000556 (2017).

41. Cascio, W. E. Wildland fire smoke and human health. *Sci. The Total. Environ.* **624**, 586–595, DOI: 10.1016/j.scitotenv.2017.12.086 (2018).

42. Kondo, M. *et al.* Meta-analysis of heterogeneity in the effects of wildfire smoke exposure on respiratory health in north america. *Int. J. Environ. Res. Public Heal.* **16**, 960, DOI: 10.3390/ijerph16060960 (2019).

43. Dedoussi, I. C., Eastham, S. D., Monier, E. & Barrett, S. R. H. Premature mortality related to united states cross-state air pollution. *Nature* **578**, 261–265, DOI: 10.1038/s41586-020-1983-8 (2020).

44. Heft-Neal, S., Driscoll, A., Yang, W., Shaw, G. & Burke, M. Associations between wildfire smoke exposure during pregnancy and risk of preterm birth in california. *Environ. Res.* **203**, 111872, DOI: 10.1016/j.envres.2021.111872 (2022).

45. Jung, Y. S. *et al.* Fine particulate matter from 2020 california wildfires and mental health–related emergency department visits. *JAMA Netw. Open* **8**, e253326, DOI: 10.1001/jamanetworkopen.2025.3326 (2025).

46. Kochi, I., Champ, P. A., Loomis, J. B. & Donovan, G. H. Valuing mortality impacts of smoke exposure from major southern california wildfires. *J. For. Econ.* **18**, 61–75, DOI: 10.1016/j.jfe.2011.10.002 (2012).

47. Wen, J. & Burke, M. Lower test scores from wildfire smoke exposure. *Nat. Sustain.* DOI: 10.1038/s41893-022-00956-y (2022).

48. Casey, J. A. *et al.* Race/ethnicity, socioeconomic status, residential segregation, and spatial variation in noise exposure in the contiguous united states. *Environ. Heal. Perspectives* **125**, 077017, DOI: 10.1289/ehp898 (2017).

49. Graff Zivin, J., Neidell, M. & Schlenker, W. Water quality violations and avoidance behavior: Evidence from bottled water consumption. *Am. Econ. Rev.* **101**, 448–453, DOI: 10.1257/aer.101.3.448 (2011).

50. Deschênes, O., Greenstone, M. & Shapiro, J. S. Defensive investments and the demand for air quality: Evidence from the NOx budget program. *Am. Econ. Rev.* **107**, 2958–2989, DOI: 10.1257/aer.20131002 (2017).

51. Sun, C., Kahn, M. E. & Zheng, S. Self-protection investment exacerbates air pollution exposure inequality in urban china. *Ecol. Econ.* **131**, 468–474, DOI: 10.1016/j.ecolecon.2016.06.030 (2017).

52. Zhang, J. & Mu, Q. Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *J. Environ. Econ. Manag.* **92**, 517–536, DOI: 10.1016/j.jeem.2017.07.006 (2018).

53. Ito, K. & Zhang, S. Willingness to pay for clean air: Evidence from air purifier markets in china. *J. Polit. Econ.* **128**, 1627–1672, DOI: 10.1086/705554 (2020).

54. Baylis, P. & Boomhower, J. Mandated vs. voluntary adaptation to natural disasters: The case of u.s. wildfires. *NBER Work. Pap. 29621* DOI: 10.3386/w29621 (2021).

55. Boustan, L. P., Kahn, M. E. & Rhode, P. W. Moving to higher ground: Migration response to natural disasters in the early twentieth century. *Am. Econ. Rev.* **102**, 238–244, DOI: 10.1257/aer.102.3.238 (2012).

56. Zheng, S. & Kahn, M. E. Land and residential property markets in a booming economy: New evidence from beijing. *J. Urban Econ.* **63**, 743–757, DOI: 10.1016/j.jue.2007.04.010 (2008).

57. Bayer, P., Keohane, N. & Timmins, C. Migration and hedonic valuation: The case of air quality. *J. Environ. Econ. Manag.* **58**, 1–14, DOI: 10.1016/j.jeem.2008.08.004 (2009).

58. Hornbeck, R. & Naidu, S. When the levee breaks: Black migration and economic development in the american south. *Am. Econ. Rev.* **104**, 963–990, DOI: 10.1257/aer.104.3.963 (2014).

59. Tan Soo, J.-S. Valuing air quality in indonesia using households' locational choices. *Environ. Resour. Econ.* **71**, 755–776 (2018).

60. Freeman, R., Liang, W., Song, R. & Timmins, C. Willingness to pay for clean air in china. *J. Environ. Econ. Manag.* **94**, 188–216, DOI: 10.1016/j.jeem.2019.01.005 (2019).

61. Khanna, G., Liang, W., Mobarak, A. M. & Song, R. The productivity consequences of pollution-induced migration in china. *NBER Work. Pap. 28401* DOI: 10.3386/w28401 (2021).

62. Chen, S., Oliva, P. & Zhang, P. The effect of air pollution on migration: Evidence from china. *J. Dev. Econ.* **156**, 102833, DOI: 10.1016/j.jdeveco.2022.102833 (2022).

63. Neidell, M. Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. *J. Hum. Resour.* **44**, 450–478 (2009).

64. Graff Zivin, J. & Neidell, M. Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *J. Environ. Econ. Manag.* **58**, 119–128, DOI: 10.1016/j.jeem.2009.03.001 (2009).

65. Chen, S., Chen, Y., Lei, Z. & Tan-Soo, J.-S. Chasing clean air: Pollution-induced travels in china. *J. Assoc. Environ. Resour. Econ.* **8**, 59–89, DOI: 10.1086/711476 (2021).

66. Deschênes, O. & Greenstone, M. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *Am. Econ. Journal: Appl. Econ.* **3**, 152–185, DOI: 10.1257/app.3.4.152 (2011).

67. Deschênes, O. Temperature, human health, and adaptation: A review of the empirical literature. *Energy Econ.* **46**, 606–619, DOI: 10.1016/j.eneco.2013.10.013 (2014).

68. Barreca, A., Clay, K., Deschênes, O., Greenstone, M. & Shapiro, J. S. Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *Am. Econ. Rev.* **105**, 247–251, DOI: 10.1257/aer.p20151028 (2015).

69. Barreca, A., Clay, K., Deschenes, O., Greenstone, M. & Shapiro, J. S. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *J. Polit. Econ.* **124**, 105–159, DOI: 10.1086/684582 (2016).

70. Burke, M. & Emerick, K. Adaptation to climate change: Evidence from US agriculture. *Am. Econ. Journal: Econ. Policy* **8**, 106–140, DOI: 10.1257/pol.20130025 (2016).

71. Massetti, E. & Mendelsohn, R. Measuring climate adaptation: Methods and evidence. *Rev. Environ. Econ. Policy* **12**, 324–341, DOI: 10.1093/reep/rey007 (2018).

72. Carleton, T. *et al.* Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Q. J. Econ.* **137**, 2037–2105, DOI: 10.1093/qje/qjac020 (2022).

73. Lai, W., Li, S., Liu, Y. & Barwick, P. J. Adaptation mitigates the negative effect of temperature shocks on household consumption. *Nat. Hum. Behav.* **6**, 837–846, DOI: 10.1038/s41562-022-01315-9 (2022).

74. Moretti, E. & Neidell, M. Pollution, health, and avoidance behavior evidence from the ports of los angeles. *J. Hum. Resour.* **46**, 154–175 (2011).

75. Plantinga, A. J., Walsh, R. & Wibbenmeyer, M. Priorities and effectiveness in wildfire management: Evidence from fire spread in the western united states. *J. Assoc. Environ. Resour. Econ.* **9**, 603–639, DOI: 10.1086/719426 (2022).

76. Anderson, S., Plantinga, A. J. & Wibbenmeyer, M. Inequality in agency response: Evidence from salient wildfire events. *The J. Polit.* DOI: 10.1086/722044 (2022).

77. Lennon, C. Property and suppression costs. *Work. Pap.* (2022).

78. Wibbenmeyer, M. & Robertson, M. The distributional incidence of wildfire hazard in the western united states. *Environ. Res. Lett.* **17**, 064031, DOI: 10.1088/1748-9326/ac60d7 (2022).

79. Borgschulte, M., Molitor, D. & Zou, E. Y. Air pollution and the labor market: Evidence from wildfire smoke. *The Rev. Econ. Stat.* 1–46, DOI: 10.1162/rest_a_01243 (2022).

80. NOAA Office of Satellite and Product Operations. Hazard mapping system (2022).

81. SafeGraph. Weekly patterns (2022).

82. Manson, S., Schroeder, J., Van Riper, D., Kugler, T. & Ruggles, S. IPUMS national historical geographic information system: Version 17.0 [dataset], DOI: http://doi.org/10.18128/D050.V17.0 (2022).

83. Miller, N., Molitor, D. & Zou, E. Blowing smoke: Health impacts of wildfire plume dynamics. *Work. Pap.* (2017).

84. Chen, M. K. & Rohla, R. The effect of partisanship and political advertising on close family ties. *Science* **360**, 1020–1024, DOI: 10.1126/science.aaq1433 (2018).

85. Allcott, H. *et al.* Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *J. Public Econ.* **191**, 104254, DOI: 10.1016/j.jpubeco.2020.104254 (2020).

86. Dave, D., Friedson, A. I., Matsuzawa, K. & Sabia, J. J. When do shelter-in-place orders fight covid-19 best? policy heterogeneity across states and adoption time. *Econ. Inq.* **59**, 29–52, DOI: 10.1111/ecin.12944 (2020).

87. Jay, J. *et al.* Neighbourhood income and physical distancing during the COVID-19 pandemic in the united states. *Nat. Hum. Behav.* **4**, 1294–1302, DOI: 10.1038/s41562-020-00998-2 (2020).

88. Long, E. F., Chen, M. K. & Rohla, R. Political storms: Emergent partisan skepticism of hurricane risks. *Sci. Adv.* **6**, DOI: 10.1126/sciadv.abb7906 (2020).

89. Weill, J. A., Stigler, M., Deschenes, O. & Springborn, M. R. Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proc. Natl. Acad. Sci.* **117**, 19658–19660, DOI: 10.1073/pnas.2009412117 (2020).

90. Bullinger, L. R., Carr, J. B. & Packham, A. COVID-19 and crime. *Am. J. Heal. Econ.* **7**, 249–280, DOI: 10.1086/713787 (2021).

91. Fajgelbaum, P. D., Khandelwal, A., Kim, W., Mantovani, C. & Schaal, E. Optimal lockdown in a commuting network. *Am. Econ. Rev. Insights* **3**, 503–522, DOI: 10.1257/aeri.20200401 (2021).

92. Goolsbee, A. & Syverson, C. Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *J. Public Econ.* **193**, 104311, DOI: 10.1016/j.jpubeco.2020.104311 (2021).

93. Ilin, C. *et al.* Public mobility data enables COVID-19 forecasting and management at local and global scales. *Sci. Reports* **11**, DOI: 10.1038/s41598-021-92892-8 (2021).

94. Zhao, M., Holtz, D. & Aral, S. Interdependent program evaluation: Geographic and social spillovers in COVID-19 closures and reopenings in the United States. *Sci. Adv.* **7**, DOI: 10.1126/sciadv.abe7733 (2021).

95. Parolin, Z. & Lee, E. K. Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nat. Hum. Behav.* **5**, 522–528, DOI: 10.1038/s41562-021-01087-8 (2021).

96. Chen, M. K., Haggag, K., Pope, D. G. & Rohla, R. Racial disparities in voting wait times: Evidence from smartphone data. *The Rev. Econ. Stat.* 1–10, DOI: 10.1162/rest_a_01012 (2022).

97. Tai, X. H., Mehra, S. & Blumenstock, J. E. Mobile phone data reveal the effects of violence on internal displacement in afghanistan. *Nat. Hum. Behav.* **6**, 624–634, DOI: 10.1038/s41562-022-01336-4 (2022).

98. Glaeser, E. L., Gorback, C. & Redding, S. J. JUE insight: How much does COVID-19 increase with mobility? evidence from new york and four other u.s. cities. *J. Urban Econ.* **127**, DOI: 10.1016/j.jue.2020.103292 (2022).

99. Valentino-Devries, J., Singer, N., Keller, M. H. & Krolik, A. Your apps know where you were last night, and they're not keeping it secret. *The New York Times* (2018).

100. Thompson, S. A. & Warzel, C. One nation, tracked. *The New York Times* (2019).

101. Thompson, Y., Stuart A. Serkez & Kelley, L. How has your state reacted to social distancing? *The New York Times* (2020).

102. Squire, R. F. Measuring and correcting sampling bias in safegraph patterns for more accurate demographic analysis. (2019).

103. Squire, R. F. What about bias in the safegraph dataset? (2019).

104. Wen, J. & Burke, M. Wildfire smoke plume segmentation using geostationary satellite imagery, DOI: 10.48550/ARXIV.2109.01637 (2021).

105. Wildland Fire Interagency Geospatial Service. Wildland fire perimeters full history (2022).

106. SafeGraph. Patterns: Privacy (2022).

107. Anderton, D. L., Anderson, A. B., Oakes, J. M. & Fraser, M. R. Environmental equity: The demographics of dumping. *Demography* **31**, 229–248, DOI: 10.2307/2061884 (1994).

108. Banzhaf, S., Ma, L. & Timmins, C. Environmental justice: The economics of race, place, and pollution. *J. Econ. Perspectives* **33**, 185–208, DOI: 10.1257/jep.33.1.185 (2019).

Acknowledgements

The authors have no relevant funding to acknowledge.

Author contributions statement

All authors contributed to the conception, design, analysis, and writing of the study. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Extended data, Supplementary information, and Supporting code will be made available upon publication.

Correspondence and requests for materials should be addressed to Edward Rubin.

A Methods

A.1 Data

Unit of analysis CBGs provide an advantageous unit of analysis in our setting for several reasons. First, most CBGs delineate compact geographic areas containing small populations (typically 600–3,000 individuals). Smaller areas reduce aggregation-related errors when we assign smoke exposure, migratory behavior, and socioeconomic measurements to entire CBGs.[11] To maximize this 'match'—*i.e.*, to keep CBGs' areas small—we focus on urban CBGs—where urban population exceeds rural population. The resulting panel covers 27,555 urban CBGs throughout California, Oregon, and Washington (2018–2021)—comprising 91.3% of the US's west-coast CBGs, 93.3% of the population (47.1 million people), and 93.9% of SafeGraph visits (3 billion).[12]

Movement data We measure communities' short-term migration patterns using SafeGraph's aggregated and anonymized cellphone-movement data[81]. Specifically, we use SafeGraph's *Weekly Patterns* dataset, which monitors 45 million cellphones' 'visits' to 3.6 million Points-of-Interest (POIs). A POI represents any *visitable* location—*e.g.*, restaurants, schools, parks, doctors' offices. Across the 30,174 west-coast CBGs in our data, we observe 3.2 billion visits to POIs during 2018–2021. SafeGraph uses internal microdata (similar to data in[84]) to predict a home CBG for each cellphone. The Weekly Patterns dataset contains the number of visits to each POI by the visitors' home CBGs—during each week. From these counts, we calculate our main measure of out-migration: the percentage of a CBG's visits (each week) that occurred outside of the CBG's county.

Our second out-migration measure uses the 75th percentile of distances traveled by a CBG's residents—measured between CBG and POI centroids—to proxy for the distance traveled away from home by residents of each CBG each week. Panel C of Figure 1 (and Table S1) shows approximately 22% of POI visits occur outside individuals' home counties. Thus, the 75th-percentile distance measure allows us to measure how much farther people are traveling due to smoke—focusing on the part of the distance distribution likely to be affected. Together, these data and calculations provide a unique, spatially resolved view of communities' weekly travel behaviors across four years.

Our cellphone-based movement data offer several strengths for our analysis relative to more traditional datasets. First, movement data provide insights into human behaviors that are largely unavailable—particularly at the scale (10% of the smartphone market) and frequency (all day, every day) of the SafeGraph data. Second, their scale and frequency generate sufficient statistical power to estimate unequal/heterogeneous responses to infrequent events. Answering equity questions about wildfire-smoke exposure requires this power. Finally, the data are *revealed* behaviors—likely suffering less from recall or dishonesty. The strengths of these data are evidenced by the volume of recently published studies that use them[2,84–98].

Cellphone-based movement data are not without concerns and limitations. Some issues relate to the strength of the data—many authors raise ethical and practical concerns for cellphone-based data[99].[13] To

[11] CBGs are the smallest unit at which we could obtain cellphone-based movement data—our out-migration measure—and some socioeconomic data.

[12] Tables S1 and S2 summarize demographics, smoke exposures, and visits for *urban* West Coast CBGs and *all* West Coast CBGs—by CBG (Panel A) and by CBG-week (Panel B).

[13] Some prominent early critics of cellphone-based data later published work using cellphone-based data (see[100] and later[101]).

address some privacy concerns, SafeGraph does not distribute microdata and applies differential-privacy techniques to many features of their aggregated data. Supplemental Materials section B.3 further describes SafeGraph's differential-privacy approach and why it is unlikely to affect our results substantially. Another common concern is external validation—how representative is this sample of 45 million cellphone users? SafeGraph's internal calculations suggest the sample of phones is reasonably balanced at the CBG for income, race, and ethnicity[102,103]. More conservatively: the sample is internally valid for the 45 million users in the dataset—a sizable share of the adult population in the US. In our context, the costs associated with aggregated and already-available movement data seem small; with these data, the study is possible.

Smoke exposure data We calculate CBGs' weekly smoke exposures using smoke-plume shapefiles from the US National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS) Fire and Smoke Product[80]. These publicly available data provide daily records of smoke-plume boundaries across North America throughout the sample period.[14] We consider CBG i to be exposed to smoke in week w if any smoke plumes from week w intersect with a i's boundaries. While coarse[104], numerous studies find communities' and individuals' HMS-based smoke exposure significantly correlate with human responses—*e.g.*,[2,44,79,83]. We also use historical data from the Wildland Fire Interagency Geospatial Services[105] to determine CBGs located near past wildfires.

Smoke exposure varies substantially throughout the sample period—in both the locations and levels of exposure. Panel B of Figure 1 depicts the percent of the west-coast population exposed to smoke in each week of 2018–2021 (colored by the intensity of smoke). This population-smoke-exposure time series includes substantial variation—ranging from weeks with nearly 0% exposure to several weeks with full-population exposure. Panel A of Figure 1 maps the number of weeks of smoke exposure (2018–2021) for each west-coast CBG. Most CBGs faced smoke during 40–80 weeks throughout the sample—though CBGs in central California and southern/eastern Oregon faced smoke during more than 100 weeks. Together, these figures illustrate the spatiotemporal variation in smoke exposure we use to identify communities' responses to smoke.

Demographic data: Five-Year American Community Survey Our data on CBGs' racial, ethnic, and income compositions come from the American Community Survey (ACS) 5-year estimates from 2019. The 2019 five-year ACS estimates aggregate the prior five years of survey data collected by the US Census Bureau in the ACS. The five-year estimates offer the advantage of supplying CBG-level data spanning the entire US—the shorter time span 1-year estimates are restricted to higher population areas. Five-year estimates likely better match the 'real-time' demographics of the sample period than the 2010 decennial census. The relevant 2020 decennial data were not available at the time of analysis.

Finally, the Census censors both ends of the ACS data on CBG-level median household income (below \$2,500 and above \$250,000)—as is evident in the summary-statistic tables (Tables S1 and S2).

Specifically, for each CBG, we use the population counts of Black, Hispanic, and White individuals and each CBG's median household income. Our main analyses focus on 'urban' CBGs, where the urban population exceeds the rural population. Data on rural and urban populations come from 2010 decennial census data from NHGIS[82].

[14]The data originate as satellite imagery from NOAA's/NASA's Geostationary Operational Environmental Satellite System (GOES); NOAA analysts then hand-draw plume boundaries—categorizing smoke density as low, medium, or high.

A.2 Empirical strategy

Model Our goal is to estimate (1) the causal effect of smoke on short-term migration and (2) how this smoke-induced migration varies by a community's racial, ethnic, or income composition.

Toward this goal, we estimate the model

$$\text{Migration}_{iw} = \beta\,\text{Smoke}_{iw} + \delta\,\text{Smoke}_{iw} \times \text{Percentile}_i + \alpha_i + \gamma_w + \varepsilon_{iw} \tag{1}$$

where Migration_{iw} measures the intensity of out-migration among residents of CBG i in week w, and Smoke_{iw} represents an indicator variable for whether CBG i encountered *any* smoke during week w.

Measurement We measure out-migration in two ways. First, we use the percentage of POI visits by residents of CBG i in week w that occur outside of i's county. Our second measure of out-migration is the 75$^{\text{th}}$ percentile of distances traveled by CBG i's residents in week w. Together, these two measures illustrate how the composition and shape of CBGs' travel distributions change when their residents face wildfire smoke.

Percentile_i refers to CBG i's rank-based percentile along one of several measurements of CBG i's socioeconomic composition (median household income; or population-share Black, Hispanic, or White). We integrate these percentiles with two alternative specifications. The first specification defines Percentile_i as numeric—*i.e.*, imposing linearity in percentile. Chetty *et al.* (2014) find intergenerational mobility is linear in individuals' income percentiles[25]; several of our results also suggest approximate linearity. However, we also relax this linearity assumption. Specifically, we apply a semi-parametric specification where Percentile_i represents a set of indicators for each mutually exclusive two-percentile group (*i.e.*, indicators that identify the bins [0%, 1%), [1%, 2%), *etc.*). We present the results for these two approaches in sequence.

CBG-specific fixed effects (FEs) (α_i) absorb time-invariant differences in out-migration across CBGs. Week-of-sample FEs (γ_w) account for out-migration shocks and seasonality common to western CBGs. Our results are robust to various fixed-effects specifications—*e.g.*, replacing α_i with a FE for *CBG by month-of-year*. Finally, ε_{iw} is the error term. Both Smoke_{iw} and other determinants of out-migration (in ε_{iw}) may correlate across weeks within a CBG and across CBGs in a given week. To account for this correlation in our inference, we estimate cluster-robust standard errors that allow for correlation within county and within calendar months (*e.g.*, July).

The parameters β and δ directly map to our central empirical questions. If $\beta > 0$, then smoke increases the out-migration. If $\delta \neq 0$, communities differ in their out-migration behavior along the dimension given by Percentile_i: larger δs imply greater tendencies to out-migrate in the presence of smoke.[15]

Identification We estimate Equation 1 using least squares regression, which amounts to the two-way fixed effects (TWFE) estimator. The TWFE estimator is unbiased/consistent for estimating our parameter of interest so long as smoke exposure is exogenous conditional on the fixed effects—*i.e.*, after controlling for CBG and week-of-sample fixed effects, there are no omitted factors that (i) directly affect a community's level of out-migration and (ii) correlate with the community's smoke exposure. Exogeneity in this context

[15] As described in the main text, while Equation 1 imposes linearity in modeling communities' heterogeneous smoke responses—*i.e.*, an increase in one percentile increases out-migration by $\delta/100$—we also relax this linearity by creating indicators of two-percentile bins.

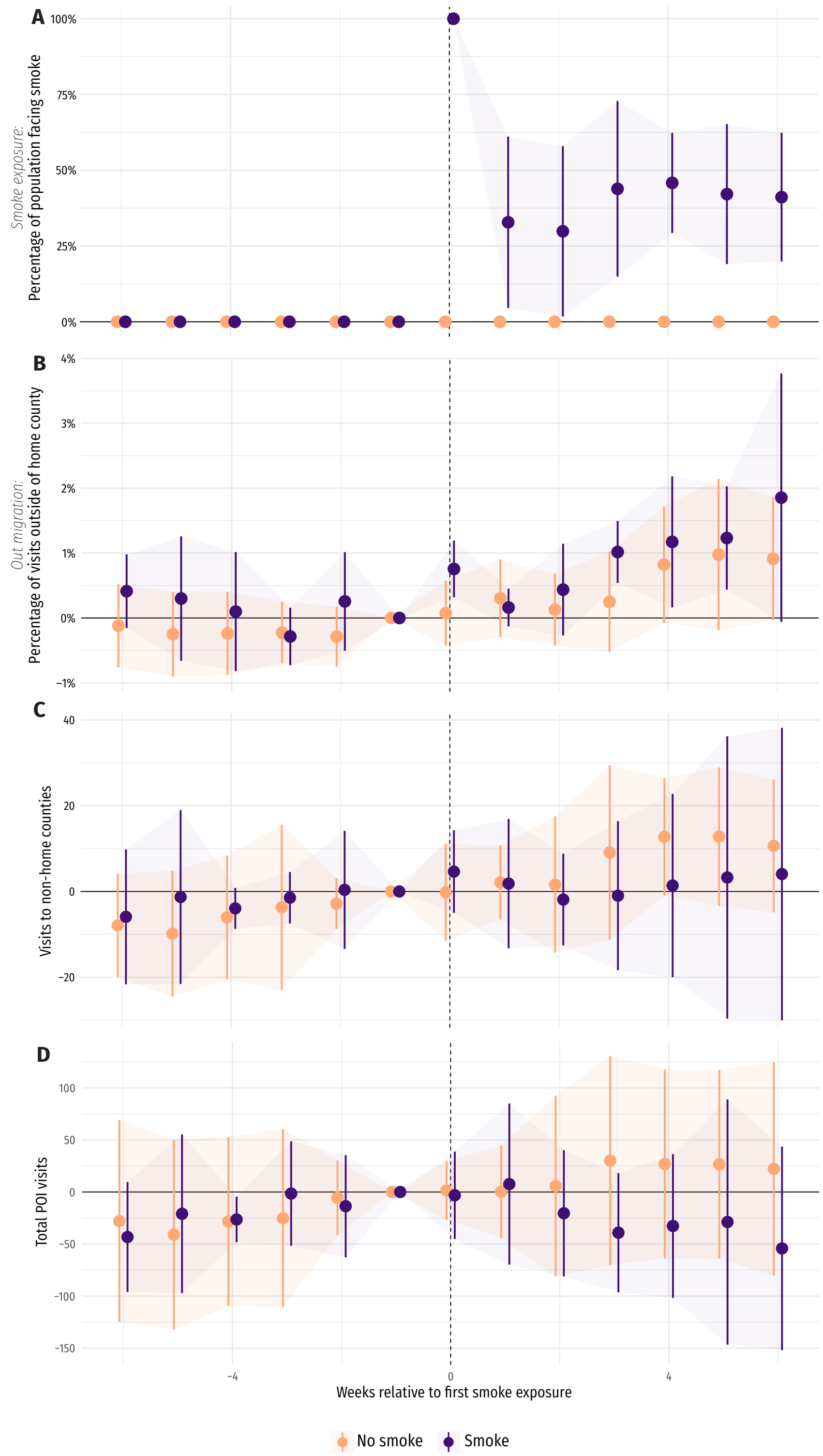
is plausibly satisfied as (1) wildfires themselves are largely unpredictable and (2) their smoke plumes are even more idiosyncratic as they are a product of wildfire location and numerous meteorological patterns. Importantly, the fixed effects remove variation from seasonality (*e.g.*, summer vacation) and cross-sectional differences (*e.g.*, affluent, fire-prone areas), ruling out many potential confounds. Finally, event studies centered on communities' *first* smoke exposures of each calendar year show immediate increases in out-migration (the share and the level of visits to non-home counties) beginning in the first week of smoke exposure (Figure S1). These event studies confirm increases in (A) smoke exposure, (B) the share of out-of-county visits, and (C) the number of visits outside of individuals' home counties. Based upon this evidence and reasoning, we believe the requisite assumption to interpret β as causal is plausible.

Interpreting out-migration behavior Our results provide evidence that communities' shares of non-home-county visits increase when affluent and historically advantaged communities face wildfire smoke. This outcome—the percentage of visits beyond residents' home counties—is the ratio of (a) the number of POI visits to other counties to (b) the total number of POI visits. Thus, a decrease in the denominator (the total number of visits) could spuriously cause this ratio to increase. To investigate this concern, we construct 13-week time-series for each of these variables centered on each CBG's first encounter of wildfire smoke per calendar year. We then construct trends for the same weeks in other calendar years when the CBG was not exposed to smoke. Figure S1C suggests that the numerator (other-county visits) indeed increases due in the first week of smoke exposure. Figure S1D bears little evidence that the denominator (total visits) decline in the first week. Note that the standard errors are quite large in Figure S1, as it only uses each CBG's *first* smoke episode of a calendar year.

Inference To conduct inference, we use a two-way cluster-robust standard-error estimator that 'clusters' by county and by calendar month.[16]

Weighting and population of inference We weight observations (CBG i in week w) by CBGs' populations. Because CBG populations are not uniform, this weighting enables us to draw inferences on the population of individuals—rather than the population of CBGs.

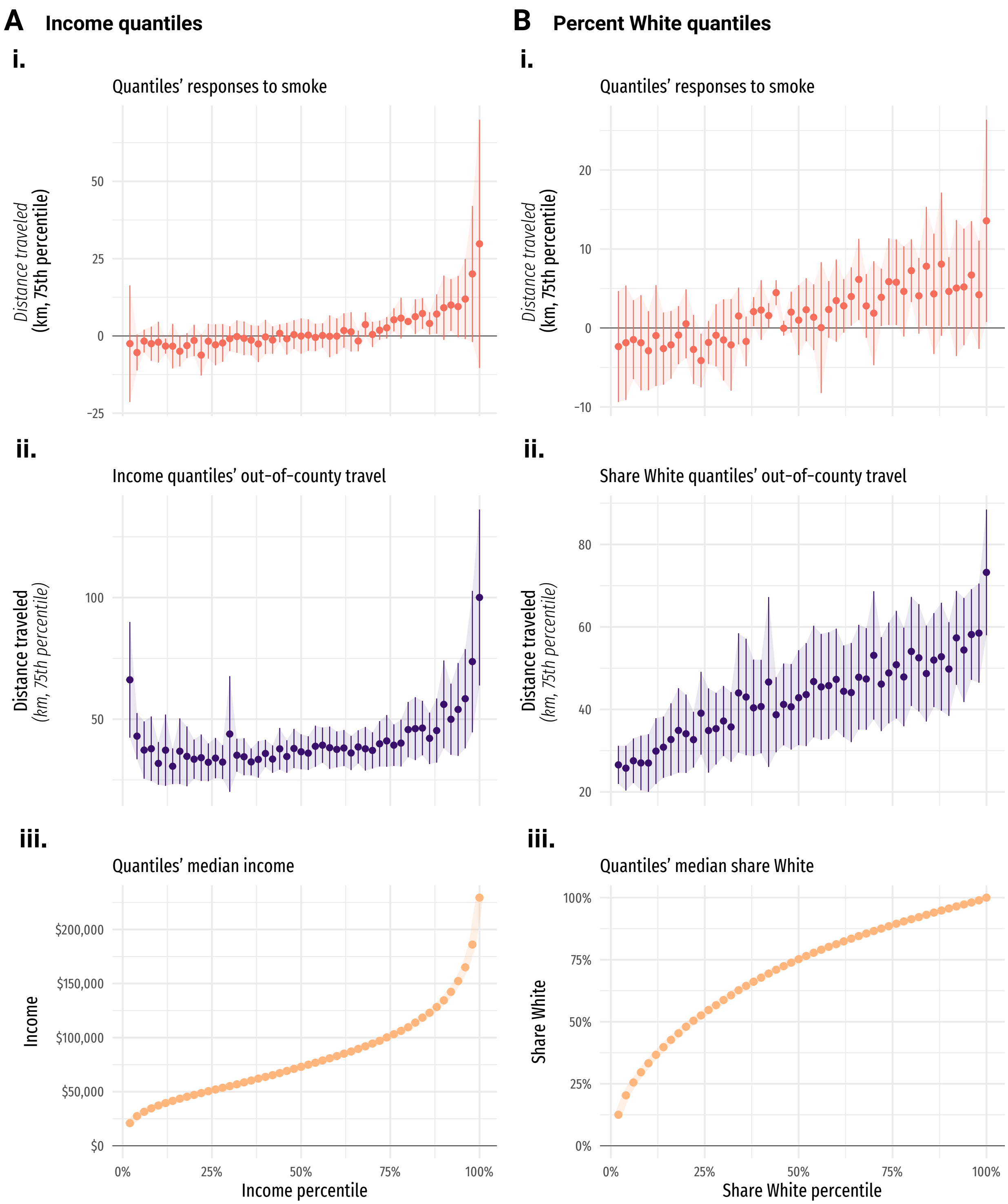
[16]Clustering within county accounts for correlated disturbances and treatment across all CBGs in the same county, across all weeks of the sample. Clustering by month of sample accounts for correlation within the given month (*e.g.*, across weeks in July 2018) and throughout that calendar month in other years (*e.g.*, July 2019).



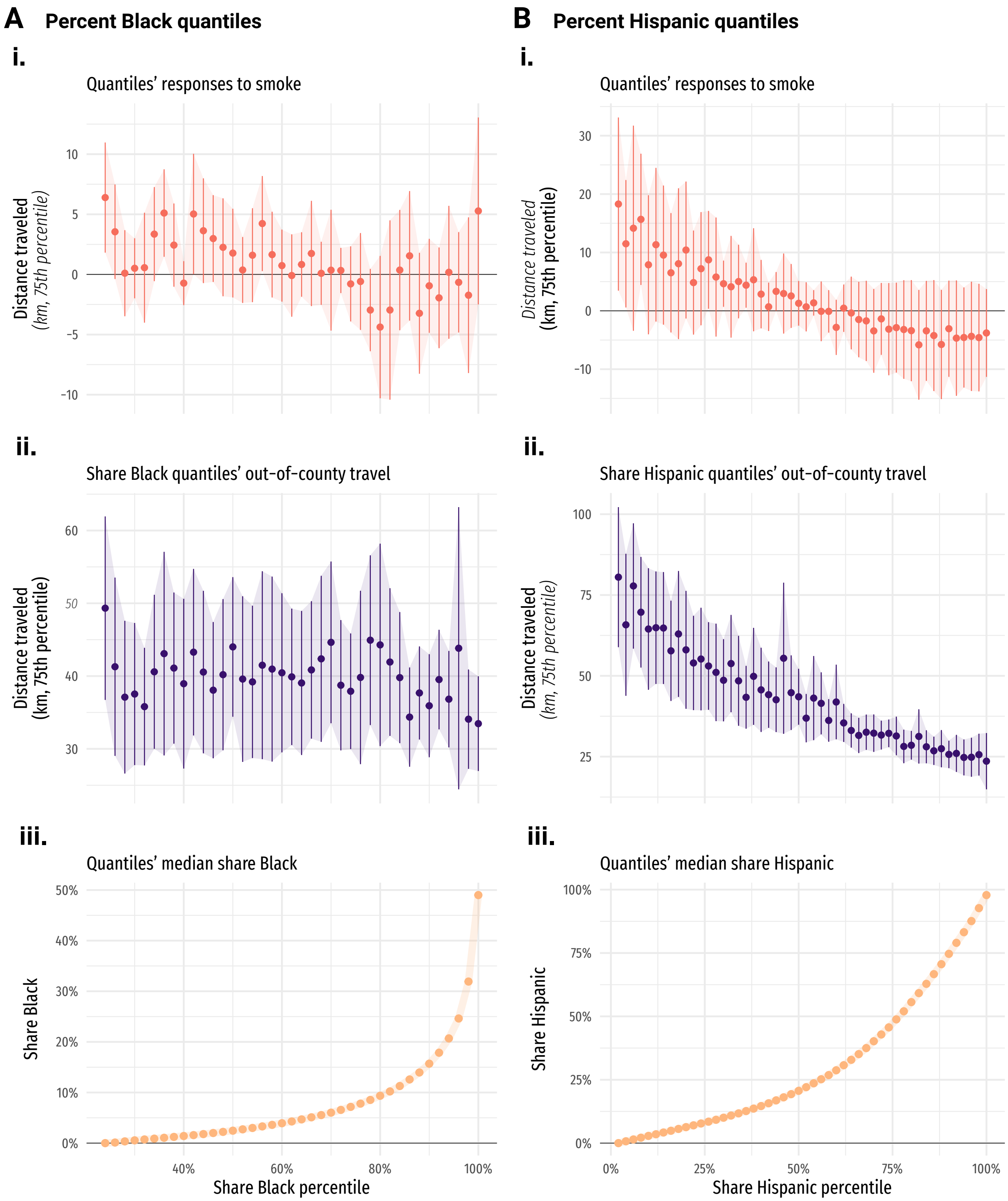
Supplementary Figure S1: Share and number of visits to non-home counties increase in first smoke week while number of total visits does not increase. Figures display trends in four outcomes (**A**: smoke; **B**: percent non-home-county POI visits; **C**: number of non-home-county POI visits; **D**: total POI visits) in the 13 weeks centered on each CBG's first encounter of wildfire smoke (in purple) for each calendar year. Orange trends depict the same weeks in other years when the CBG was not exposed to smoke.

B Supplementary information

B.1 Supplementary figures



Supplementary Figure S2: Inequality in smoke-induced out-migration using the 75th percentile of distance traveled: Income and percent White. This figure reproduces Figure 2 but with CBGs' 75th percentile of distance traveled as the outcome variable.



Supplementary Figure S3: Inequality in smoke-induced out-migration using the 75th percentile of distance traveled: Percent Black and percent Hispanic. This figure reproduces Figure 3 but with CBGs' 75th percentile of distance traveled as the outcome variable.

B.2 Supplementary tables

B.3 Privacy, noise, and censoring in SafeGraph Weekly Patterns data

The following quote from SafeGraph's *Patterns* documentation[81] describes the company's approach to manipulating their aggregated data products so as to better protect individual privacy[106].

Supplementary Table S1: Summary statistics for urban CBGs

	N obs.	Mean	Stnd. Dev.	Min.	Median	Max.
Panel A: CBG-level summaries						
POI visits						
Total	27,555	109,174.2	100,220.5	9,807	85,730	2,770,827
N within home county	27,555	84,966.2	78,177.5	2,725	67,239	2,159,970
N within home CBG	27,555	4,538.8	10,349.6	0	2,021	483,216
Travel dist. (km, *75th pctl.*)	27,555	20.4	16.6	3	17.1	1,046.7
Smoke						
Weeks of smoke	27,555	55.8	9.7	42	51	114
Population counts						
Total	27,555	1,709.8	1,063.6	0	1,492	38,754
Black	27,555	116.2	194.0	0	45	3,821
Hispanic	27,555	585.3	674.4	0	345	11,073
White	27,555	1,141.2	772.5	0	984	30,573
Rural	27,555	22.5	114.3	0	0	5,675
Urban	27,555	1,581	855.8	1	1,403	31,777
Population shares						
Black	27,545	6.7%	10.5%	0%	3%	100%
Hispanic	27,545	32.5%	27.8%	0%	23.2%	100%
White	27,545	68.4%	22.9%	0%	73.4%	100%
Rural	27,555	1.3%	5.9%	0%	0%	49.9%
Urban	27,555	98.7%	5.9%	50.1%	100%	100%
Income						
Med. HH income	26,929	$83,627.5	$43,194	$2,499	$75,017	$250,001
Panel B: CBG-by-week summaries						
POI visit counts						
All	5,758,995	522.4	523.9	4	399	23,395
Within home county	5,758,995	406.5	407.8	0	312	18,114
Within home CBG	5,758,995	21.7	59.6	0	8	17,490
Travel dist. (km, *75th pctl.*)	5,758,995	48.4	224.3	0	17.6	5,844.2
Smoke						
Any smoke	5,758,995	26.7%		0%		100%
Any 'low' smoke	5,758,995	26.6%		0%		100%
Any 'medium' smoke	5,758,995	13.6%		0%		100%
Any 'high' smoke	5,758,995	7.4%		0%		100%

Notes: This table summarizes west-coast urban CBGs, our main area of study. Table S2 summarize all west-coast CBGs (including rural CBGs). Panel A here summarizes CBG-level data; Panel B summarizes CBG-by-week data—*i.e.*, the level of analysis. We define *urban* CBGs as communities where the urban population exceeds the rural population. We omit socioeconomic data from Panel B because our demographic data (population counts/shares and income) do not vary with time. Section A.1 describes variables and sources. The *Smoke* variables in Panel B summarize indicators, so we omit the percentile summaries.

Supplementary Table S2: Summary statistics for all CBGs

	N obs.	Mean	Stnd. Dev.	Min.	Median	Max.
Panel A: CBG-level summaries						
POI visit counts						
All	30,174	106,196.6	97,906	7,295	83,509.5	2,770,827
Within home county	30,174	81,820.3	76,608.7	577	64,819	2,159,970
Within home CBG	30,174	4,374.8	10,007.7	0	1,934	483,216
Travel dist. (km, *75^{th} pctl.*)	30,174	22.9	21	3	17.8	1,046.7
Smoke						
Weeks of smoke	30,174	56.7	10.6	42	52	130
Population counts						
Total	30,174	1,673.1	1,044.7	0	1,460	38,754
Black	30,174	108.0	188.4	0	38	3,821
Hispanic	30,174	553.8	660.5	0	312	11,073
White	30,174	1,141.6	759.9	0	988	30,573
Rural	30,172	118.6	365	0	0	5,675
Urban	30,172	1,453.5	918.8	0	1,330	31,777
Population shares						
Black	30,159	6.3%	10.1%	0%	2.6%	100%
Hispanic	30,159	31.1%	27.6%	0%	21.4%	100%
White	30,159	70.3%	23.1%	0%	75.9%	100%
Rural	30,165	9.1%	26.4%	0%	0%	100%
Urban	30,165	90.9%	26.4%	0%	100%	100%
Income						
Med. HH income	29,443	$82,607.2	$42,328.3	$2,499	$73,984	$250,001
Panel B: CBG-by-week summaries						
POI visit counts						
All	6,306,366	508.1	512.2	4	388	26,695
Within home county	6,306,366	391.5	399	0	299	18,114
Within home CBG	6,306,366	20.9	57.5	0	8	17,490
Travel dist. (km, *75^{th} pctl.*)	6,306,366	53	232.4	0	18.7	5,844.2
Smoke						
Any smoke	6,306,366	27.1		0%		100%
Any 'low' smoke	6,306,366	27.1		0%		100%
Any 'medium' smoke	6,306,366	13.9		0%		100%
Any 'high' smoke	6,306,366	7.6		0%		100%

Notes: This table exands the summaries of Table S1 to all CBGs (rather than restricting to urban CBGs).

Supplementary Table S3: Robustness of regression results Adding state interaction of fixed effects

	(1)	(2)	(3)	(4)	(5)
		Percentile-based heterogeneity			
		HH Income	% Black	% Hispanic	% White
Panel A *Dependent variable: Percent of POIs visits outside of home county*					
Any smoke	0.30***	−0.41	0.54***	0.82*	0.05
	(0.09)	(0.30)	(0.14)	(0.38)	(0.20)
Any smoke × Het. percentile		1.4**	−0.46*	−0.93	0.55
		(0.53)	(0.24)	(0.67)	(0.35)
N obs. (millions)	5.63	5.63	5.63	5.63	5.63
Panel B *Dependent variable: 75th percentile of distance traveled to POIs (km)*					
Any smoke	1.4**	−7.1*	5.8**	12.9*	−3.6*
	(0.53)	(3.9)	(2.1)	(6.8)	(1.8)
Any smoke × Het. percentile		17.1**	−8.3*	−20.3	11.1**
		(7.6)	(3.8)	(11.8)	(4.7)
N obs. (millions)	5.63	5.63	5.63	5.63	5.63
Fixed effects					
CBG	✓	✓	✓	✓	✓
State × Week of sample	✓	✓	✓	✓	✓

Notes: This table re-estimates the results in Table 1 but with state by week-of-sample fixed effects.

Supplementary Table S4: Robustness of regression results Dropping CBGs directly affected by wildfires

	(1)	(2)	(3)	(4)	(5)
		Percentile-based heterogeneity			
		HH Income	% Black	% Hispanic	% White
Panel A *Dependent variable: Percent of POIs visits outside of home county*					
Any smoke	0.28^{**}	-0.41	0.55^{***}	0.90^{*}	-0.10
	(0.10)	(0.30)	(0.15)	(0.39)	(0.22)
Any smoke × Het. percentile		1.4^{**}	-0.50^{*}	-1.20	0.80^{*}
		(0.53)	(0.24)	(0.70)	(0.38)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Panel B *Dependent variable: 75^{th} percentile of distance traveled to POIs (km)*					
Any smoke	1.7^{***}	-6.9^{*}	6.0^{***}	11.7^{*}	-3.4
	(0.54)	(4.1)	(2.1)	(6.0)	(2.3)
Any smoke × Het. percentile		17.2^{**}	-8.1^{*}	-19.0	10.8^{*}
		(7.7)	(3.7)	(11.6)	(4.9)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Fixed effects					
CBG	✓	✓	✓	✓	✓
Week of sample	✓	✓	✓	✓	✓

Notes: This table re-estimates the results in Table 1 but without CBGs that were ever affected by wildfires between 2018–2021 (*i.e.*, CBG boundaries that intersect with wildfire perimeters).

To preserve privacy, we apply differential privacy techniques to the following columns: `visitor_home_cbgs`, `visitor_home_aggregation`, `visitor_daytime_cbgs`, `visitor_country_of_origin`, `device_type`, `carrier_name`. We have added Laplacian noise to the values in these columns. After adding noise, only attributes (e.g., a census block group) with at least two devices are included in the data. If there are between 2 and 4 visitors this is reported as 4.

As described in A.1, our outcome variables use the count of visitors decomposed by the visitors' home CBGs, *i.e.*, the variable `visitor_home_cbgs`. SafeGraph's differential-privacy approach likely has little effect on our estimates of the level and equity of smoke-induced migration. First, because we aggregate to CBG (across many POIs within each CBG) and SafeGraph's manipulation mainly affects low-count observations at the POI level, we still accurately account for the vast majority of visits. Second, our distance-based measurement of out-migration uses the 75^{th} percentile—*i.e.*, a measure that is relatively robust to small changes in the tails of a distribution. Finally, the differential-privacy approach affects our outcome variable (rather than an explanatory variable), so any measurement error merely ends up in the error term (rather than biasing our point estimates).

B.4 Methodological comparison with Burke *et al.* (2022)

While there is overlap, our empirical approach differs from that of Burke *et al.* (2022) in several ways[2]. First, our analysis focuses on Census Block Groups (CBGs), while Burke *et al.* aggregate to counties. This higher spatial resolution afforded by CBGs allows a finer match between communities and incomes—resolving error from aggregation/the ecological fallacy[107,108]. We also aggregate across days in a week rather than focusing on day-level outcomes. Day-level timing matches Burke *et al.*'s goal of mapping daily smoke-induced $PM_{2.5}$ to social outcomes. However, by aggregating across days, we can capture short-term intertemporal substitution of travel[64]. Intertemporal variation may be more relevant for testing our hypothesis of short-term out-migration. Our exposure variables also differ: We focus on all 'wildfire smoke,' whereas Burke *et al.* examine $PM_{2.5}$ generated by wildfire smoke. $PM_{2.5}$ undoubtedly represents a significant concern for public health. However, our goal is estimating the effect of smoke *itself*—rather than hazardous particulates caused by smoke. Finally, our outcomes differ. We measure out-migration as the share of a CBG's trips that leave the county or the 75^{th} percentile of distance traveled by the CBG's residents; Burke *et al.* focus on individuals that remain home (or are absent from their homes) for the entirety of the day (among other behaviors—*e.g.*, social media posts and internet search topics). These differences in the unit of analysis and definitions of outcomes provide a complementary view of smoke-induced out-migration.