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]. Evacuation also plays a critical role in modern natural-disaster responses[2–4]. However, nothing guarantees individuals have equal access to this strategy. Recent research highlights the importance of avoidance behaviors for hazards/disasters like wildfire smoke[5,6], floods[7–9], and hurricanes[3,10]. Yet work on inequality in the US documents marked disparities consistent with unequal avoidance opportunities—life expectancy and mortality[11–16], health[17–19], healthcare[20–22], pollution exposure[23–27], educational opportunities[28–31], transportation[32], and employment outcomes[33–37]. 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 disasters and hazards, 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[38]. 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[39–45]—potentially unraveling decades of improved air quality[46]—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[5,43] with the wildfire smoke[47–55]. 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. 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

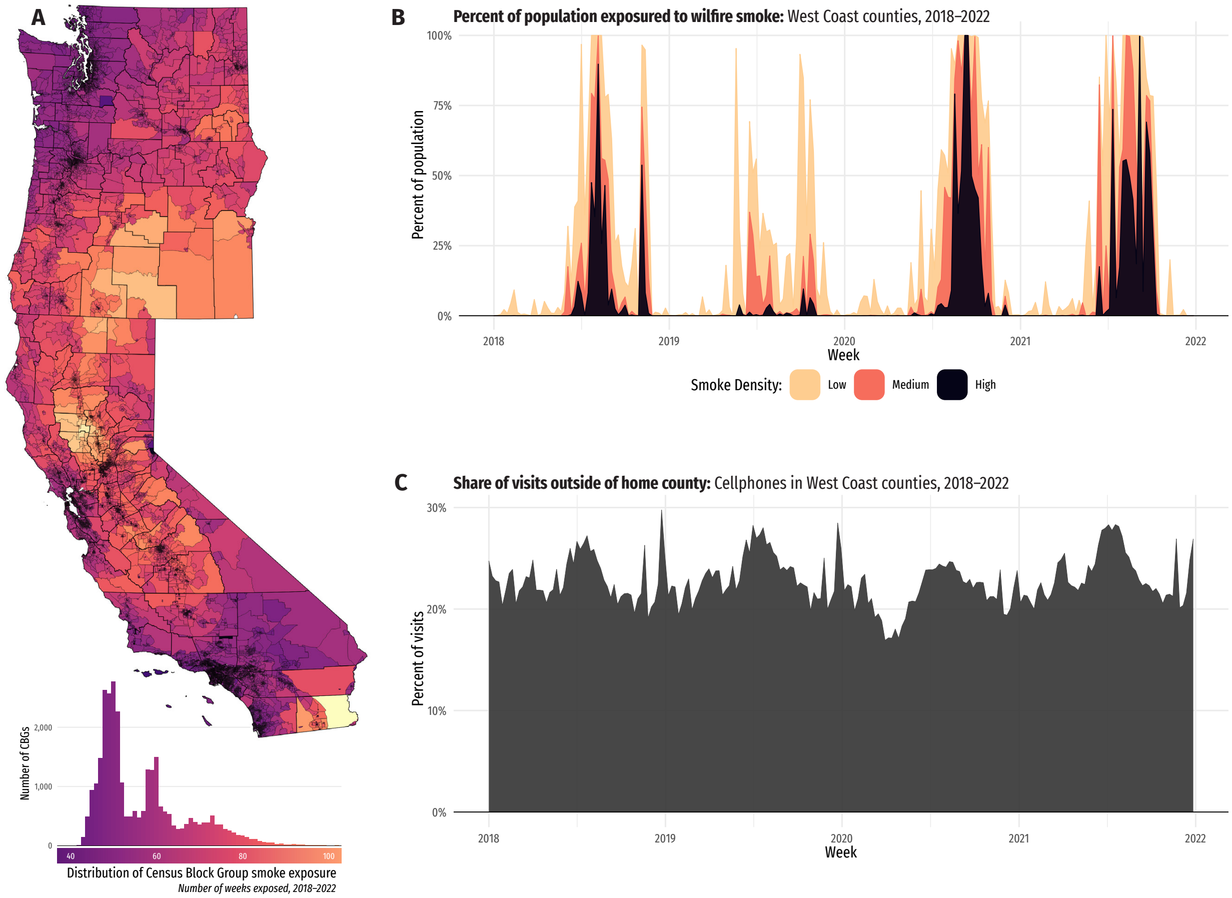

Figure 1. Spatiotemporal smoke exposure and mobility. **A** illustrates the study area—the West Coast of the United States. The smallest features in the map in **A** are shaded in proportion to the number of weeks the Census Block Groups (CBGs) experienced any wildfire smoke 2018–2021. **B** depicts 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.

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 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[23,24], air pollution[25–27], and noise[56]. 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[57], pharmaceuticals[58], masks[59,60], and air purifiers[61]) structural investments[62], long-term migration[63–70], and short-term travel[5,47,71–73]. 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[70], and more affluent individuals are more likely to make defensive investments—masks[59]. Our (short-run) migration results also relate to the climate-adaption literature[74–81]. 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[58,82]. 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[83–85], the incidence of wildfire hazard[86], the incidence of fire suppression costs[42], and the burden of wildfire smoke[87]. Limited previous work exists on avoidance behaviors in the setting of wildfires. One exception[47] 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[5]. 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, week of sample, and state-year. This estimator effectively 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. Event studies (Figure S1) and the estimated lag structure (Table S4) all support the key identifying assumption for our empirical model: the spatiotemporal arrival of wildfire smoke does not coincide with other factors that affect communities' likelihood to out-migrate (conditional on the fixed effects). Put differently: Absent exposure to wildfire smoke, out-migration patterns in exposed communities would have remained similar to unexposed communities. The unpredictability of wildfires and the factors that guide their smoke support the plausibility of this assumption. 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[88] 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[89] 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 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 75$^{\text{th}}$ 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[90]. 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 49$^{\text{th}}$ and 50$^{\text{th}}$ percentiles) to flexibly estimate heterogeneity with respect to demographics—testing whether smoke avoidance is more common or more intense within specific demographic groups.

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

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 reveals 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 75$^{\text{th}}$ percentile of distance traveled to POIs. Each column in each panel results from a separate regression with the same fixed-effect specification—CBG, week-of-sample, and state by year.[3] The standard-error estimator allows clustering within county and month-of-sample. Finally, Table 1 drops CBGs directly affected by wildfires (rather than just their smoke) during the sample period.

In Column (1) of Panel A (Table 1), we estimate that smoke significantly increases a CBG's share of out-of-county POI visits by .28 percentage points (p-value $<$ .003). 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 documents marginally significant evidence of smoke-induced out-migration—specifically, the 75$^{\text{th}}$ percentile of a CBG's distance traveled increases when CBGs face smoke (p-value .10). 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

[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. Results across the two tables are very similar.

		Percentile-based heterogeneity			
		HH Income	% Black	% Hispanic	% White
	(1)	(2)	(3)	(4)	(5)
Panel A. *Dependent variable: Percent of visits outside of home county*					
Any smoke	0.28^{***}	-0.41	0.55^{***}	0.89^{***}	-0.10
	(0.09)	(0.27)	(0.15)	(0.33)	(0.17)
Any smoke × Het. percentile		1.4^{***}	-0.50^{**}	-1.2^{*}	0.81^{***}
		(0.50)	(0.21)	(0.60)	(0.30)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Panel B. *Dependent variable: 75th percentile of distance traveled (km)*					
Any smoke	1.5	-7.1	5.8^{***}	11.4^{**}	-3.6^{*}
	(0.89)	(4.2)	(2.0)	(5.4)	(1.8)
Any smoke × Het. percentile		17.2^{**}	-8.1^{**}	-18.9^{*}	10.8^{***}
		(8.3)	(3.1)	(10.2)	(3.7)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Fixed effects					
CBG	✓	✓	✓	✓	✓
Week of sample	✓	✓	✓	✓	✓
State by year	✓	✓	✓	✓	✓

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, week-of-sample, and state-year. Observations are weighted by CBG population. Table S3 reproduces the current table with *state by week-of-sample* fixed effects. Standard errors allow clustering within county and month-of-sample. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

of 48.4 kilometers (Table S1, Panel B), implying a sizable (3.5-percent) increase in the 75th 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.

Table 1 offers 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 47th percentile of income for out-of-county travel (Panel A) and the 53rd 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-county visits for the top income percentile by 1.4 percentage points (p-value .008) and increases their 75th percentile of travel by 17.2 kilometers (p-value .04). The effects for the most-affluent communities are 3–7 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

[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 50th percentile and would have $\text{Percentile}_i = .50$.

Percentile as 50 mutually exclusive indicator variables (*i.e.*, two-percentile bins, *e.g.*, an indicator for communities in the the 49th–50th 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 50th 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 50th 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 90th 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 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 evidence that

[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).

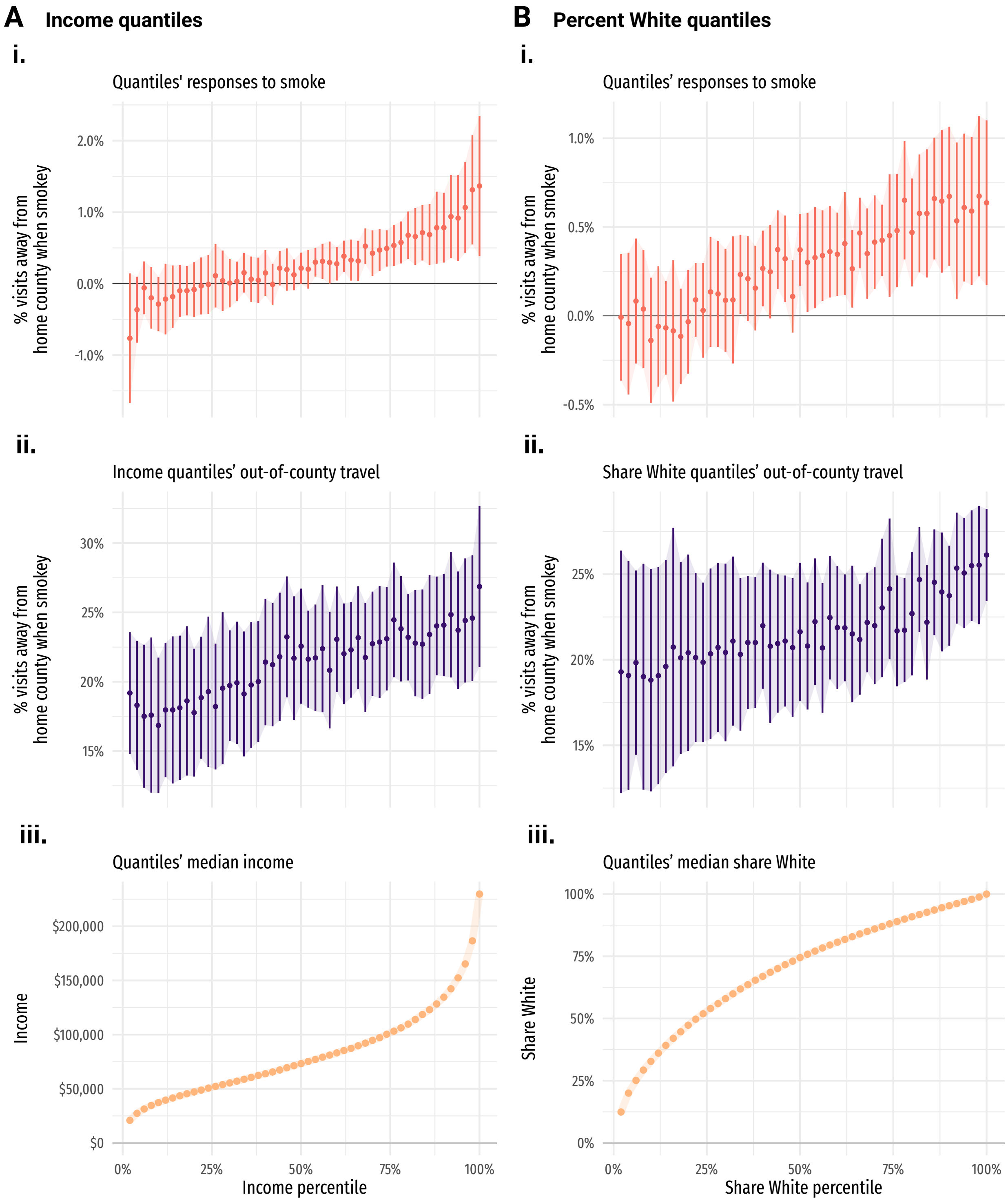

Figure 2. More affluent and more White communities are more likely to out-migrate in the presence of smoke. Panels A and B report percentile-based results by CBGs' median income or population-share White (respectively). The horizontal axis provides the percentile throughout the figure. Within each panel: 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).

smoke induces any out-migration in communities below the 30th 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 .55 (*p*-value .0006) percentage points and increases their distance traveled by 5.8 kilometers (*p*-value .005). However, the most-Black communities show no significant evidence of smoke-induced out-migration: neither in propensity to travel out-of-county nor in distance traveled. Communities that are at least seven percent Black—above 72nd percentile in the West Coast's distribution—show no significant evidence of smoke-base out-migration.

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 .89 percentage points; *p*-value .009) and in the distance traveled (increasing the 75th percentile by 11.5 kilometers; *p*-value .04). 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 26-percent Hispanic (above the 58th 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 (*i.e.*, >33% non-White residents) show no statistically significant evidence of smoke-induced out-migration. When facing wildfire smoke, the most-White urban communities (∼100% White) out-migrate significantly more than less-White communities.

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

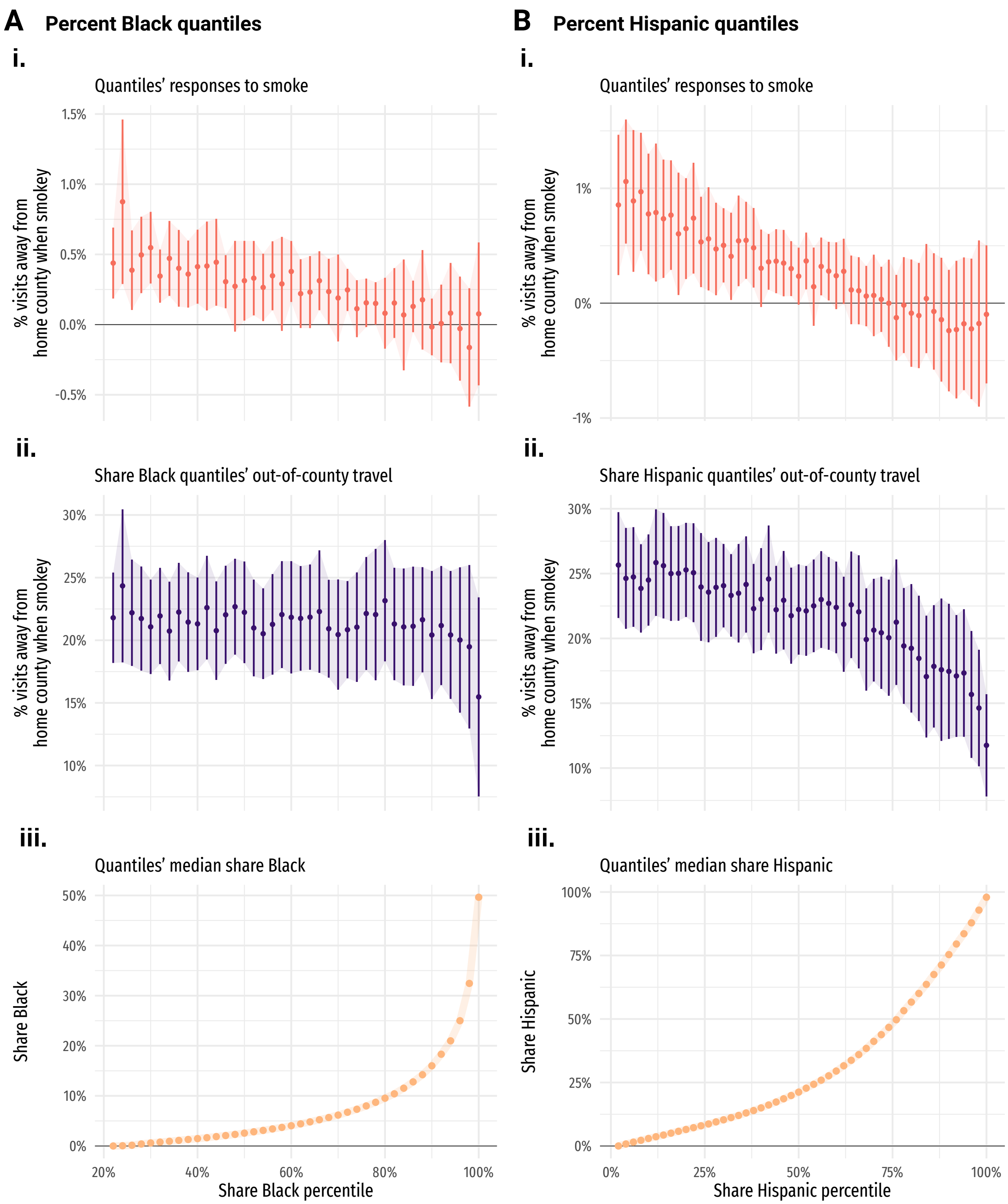

Figure 3. Black and Hispanic communities are less likely to out-migrate in the presence of smoke. This figure follows the same layout as Figure 2 but instead focuses on communities' population share Black (Panel A) or Hispanic (Panel B). The horizontal axis provides the percentile throughout the figure. 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).

Communities above the 38^{th} percentile of share White (communities that are at least 67% 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 25^{th} 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, $\sim 75^{th}$ 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.

Movement patterns 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 75^{th} percentile of distance traveled.

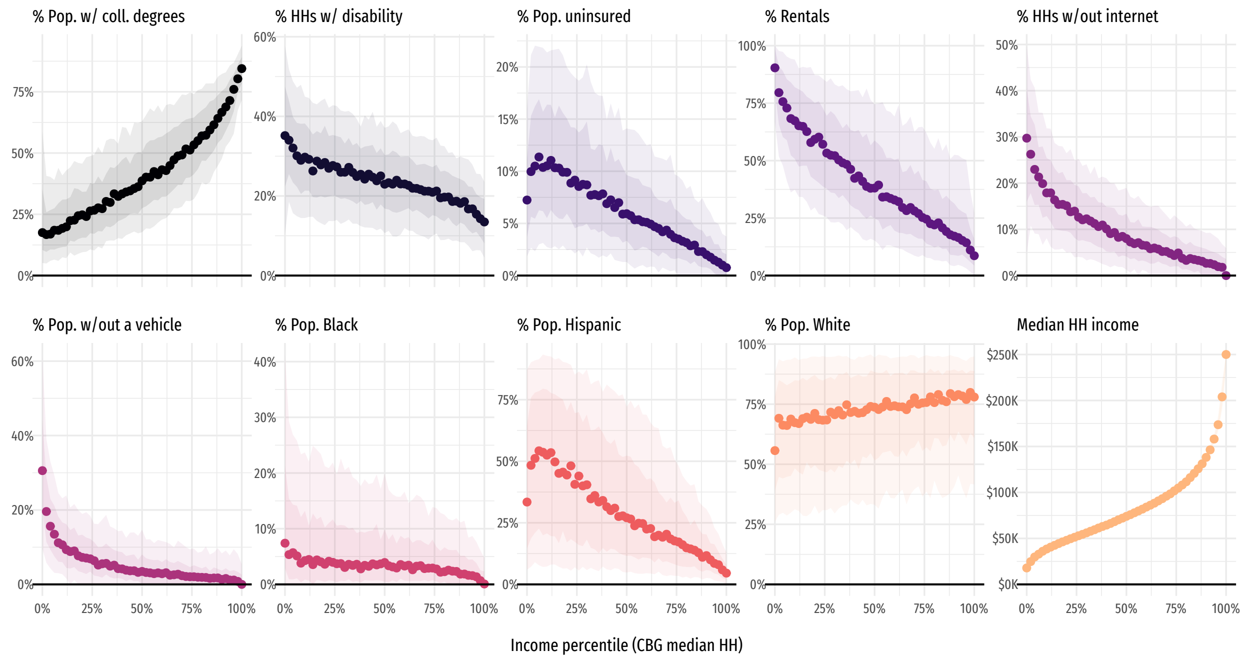

Figure 4. Urban CBG income percentile maps into many potential mechanisms among other socioeconomic dimensions. Each subfigure summarizes urban, west-coast CBGs levels of the given variable by two-percentile bins (*e.g.*, combining the first and second percentiles). Solid dots the median. The first, 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[87,91]. 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[26] 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.

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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

Supporting code and data The code for the project is available on the project Github repository `https://github.com/edrubin/smoke-migration`. Data access is restricted by a non-disclosure agreement. However, similar data are available via subscription from `Dewey`.

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[89]. 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[92]) 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[5,92–106].

Cellphone-based movement data are not without concerns and limitations. Some issues relate

[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).

to the strength of the data—many authors raise ethical and practical concerns for cellphone-based data[107].[13] To 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[110,111]. 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[88]. 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[112], numerous studies find communities' and individuals' HMS-based smoke exposure significantly correlate with human responses—*e.g.*,[5,52,87,91]. We also use historical data from the Wildland Fire Interagency Geospatial Services[113] 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

[13] Some prominent early critics of cellphone-based data later published work using cellphone-based data (see[108] and later[109]).

[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.

(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[90].

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

$$\text{Migration}_{iw} = \beta\,\text{Smoke}_{iw} + \delta\,\text{Smoke}_{iw} \times \text{Percentile}_i + \alpha_i + \gamma_w + \zeta_{s(i)y(w)} + \varepsilon_{iw} \tag{1}$$

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[33]; 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. State-year FEs $(\zeta_{s(i)y(w)})$ adjust for remaining cross-state and cross-year differences. 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]

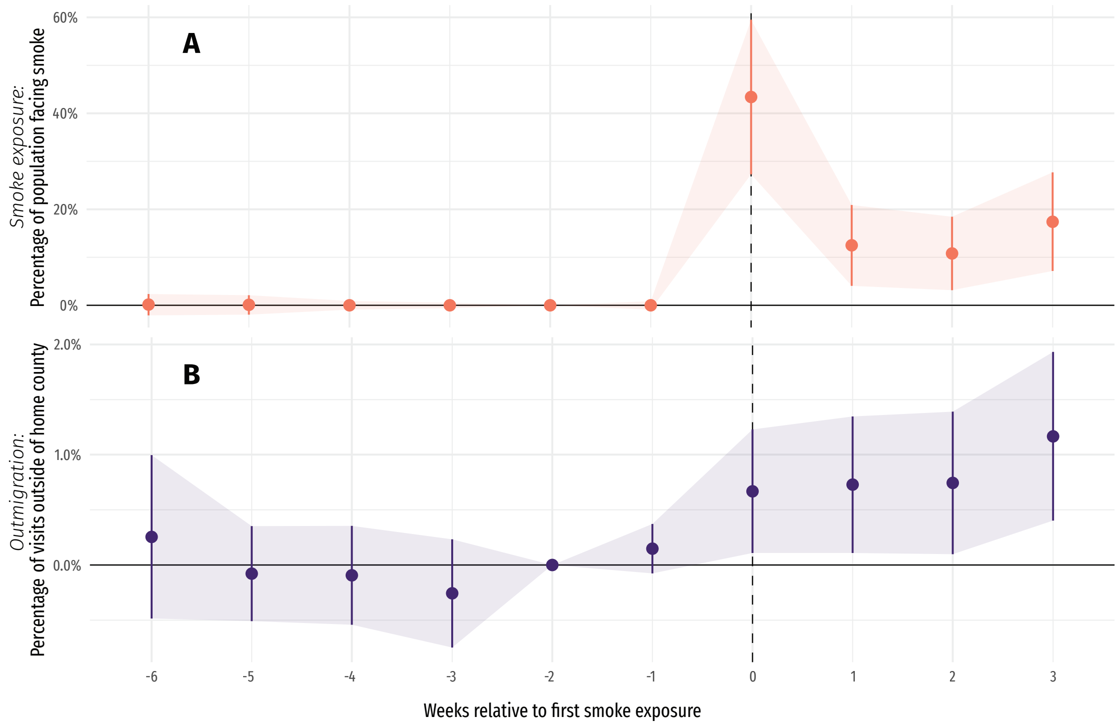
Identification We estimate Equation 1 using least squares regression, which amounts to the two-way fixed effects (TWFE) estimator. As discussed in Empirical approach, the TWFE estimator is unbiased/consistent for estimating our parameter of interest so long as smoke exposure is exogenous conditional 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 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. Additionally, the event studies in Figure S1 show out-migration immediately begins in the first week of smoke exposure. The event studies in Figure S1 broadly follow the paper's empirical approach—with CBG-by-week and state-by-year FEs—but restrict to CBG-week observations that (*i*) are part of a 10-week window with smoke arriving on week seven **or** (*ii*) entirely smokeless *and* match a week-of-year sequence from condition *i* (in a different calendar year). The CBG-week FE ensures event studies compare a smoke-exposed CBG to itself in the same calendar weeks when it did not experience smoke. Finally, the estimated structure of lagged *Any smoke* in Table S4 lends additional credibility to the empirical strategy: including additional lags of *Any smoke* does not meaningfully change the point estimate for the effect of smoke in the same week. Further, the magnitude of the point estimates declines as the lag increases. Based upon this evidence and reasoning, we believe the requisite assumption to interpret β as causal is plausible: the paper's regressions estimate the causal effect of smoke exposure on out-migration.

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 in non-home counties to (b) the total number of POI visits. A decrease in the denominator (the total number of visits) could spuriously cause this ratio to increase. To investigate this concern, we re-estimate our model (Equation 1) for outcome variables that are the counts of (1) *total visits* (the denominator), (2) *visits to other counties* (the numerator), and (3) *visits to home county*. Of the three estimates, only the number of visits to non-home counties significantly increases in the presence of wildfire smoke (Table S5)—suggesting wildfire smoke indeed (on average) increases visits to other counties.[16]

The fact that both out-migration measures (share of non-home-county visits and 75$^{\text{th}}$ percentile

[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.

[16]The coefficient on *visits to non-home counties* is also largest relative to its mean by several factors.



Supplementary Figure S1: Out-migration increase coincides with onset of smoke: Event studies Figures display event studies for two outcomes (**A**: population exposure to smoke; **B**: percent of visits to non-home-county POIs) in the 6 weeks preceding and 3 weeks following a CBG's encounter with wildfire smoke. Event studies compare a smoke-exposed CBG to itself in the same calendar weeks when it did not experience smoke.

of distance traveled) agree also supports our interpretation. Notably, both measures agree to a high degree on the pattern of positive, negative, and statistically significant coefficients in Table 1. Finally, when we estimate Equation 1 on other quartiles of distance traveled (shown in Table S6 we find no evidence that lower quartile contract (point estimates are very small and far from statistically significant). Only the 75$^{\text{th}}$ show meaningful increases with smoke—suggestive of out-migration lengthening the right tail of the distribution of distance-traveled. Together, this evidence suggests that out-migration indeed occurs in the presence of wildfire smoke.

Inference To conduct inference, we use a two-way cluster-robust standard-error estimator that 'clusters' by county and by calendar month.[17]

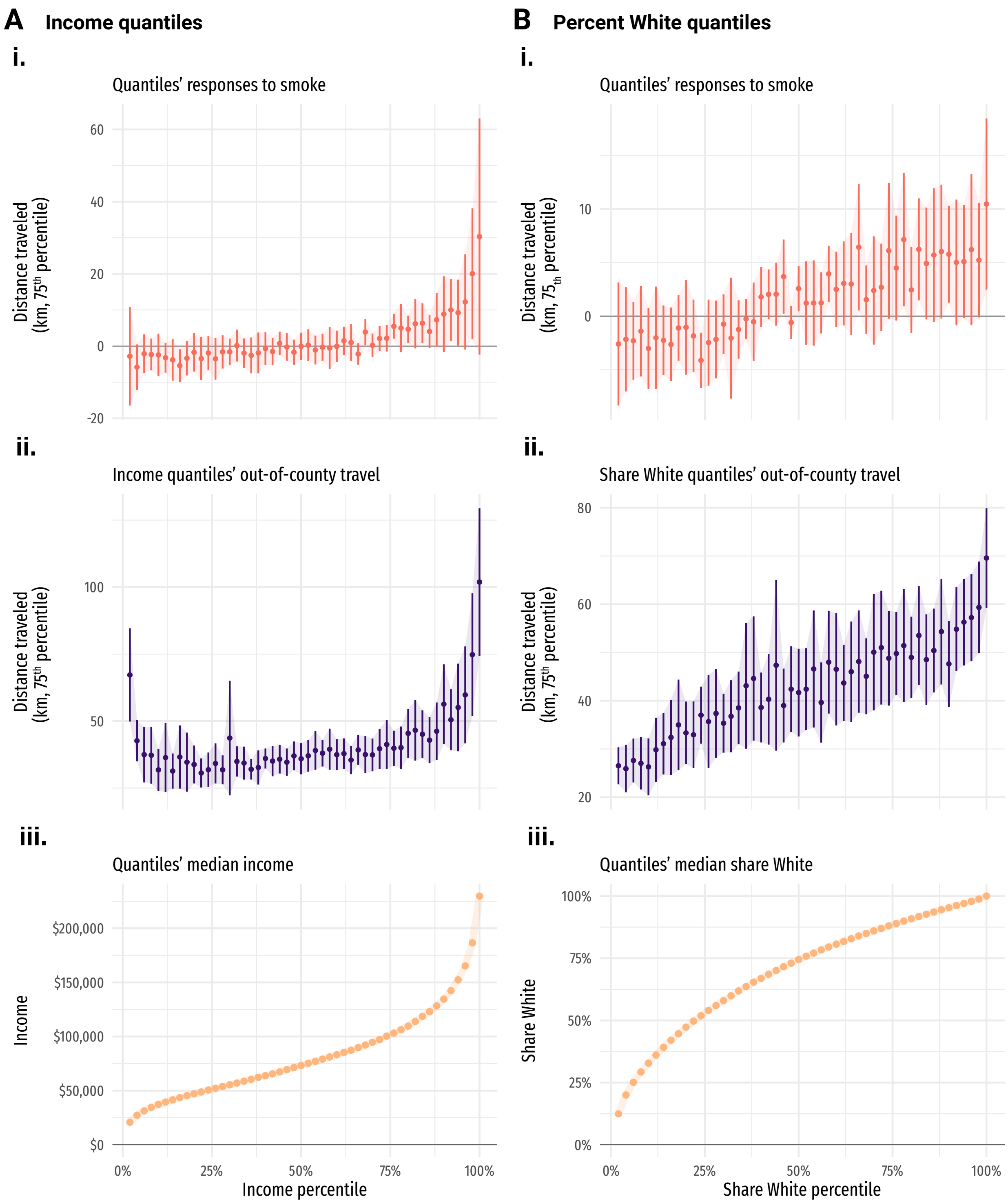
Weighting and population of inference We weight observations (CBG i in week w) by CBGs' populations. Because CBG populations are not uniform, this weighting enables us to draw inferences on the population of individuals—rather than the population of CBGs.

[17] 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).

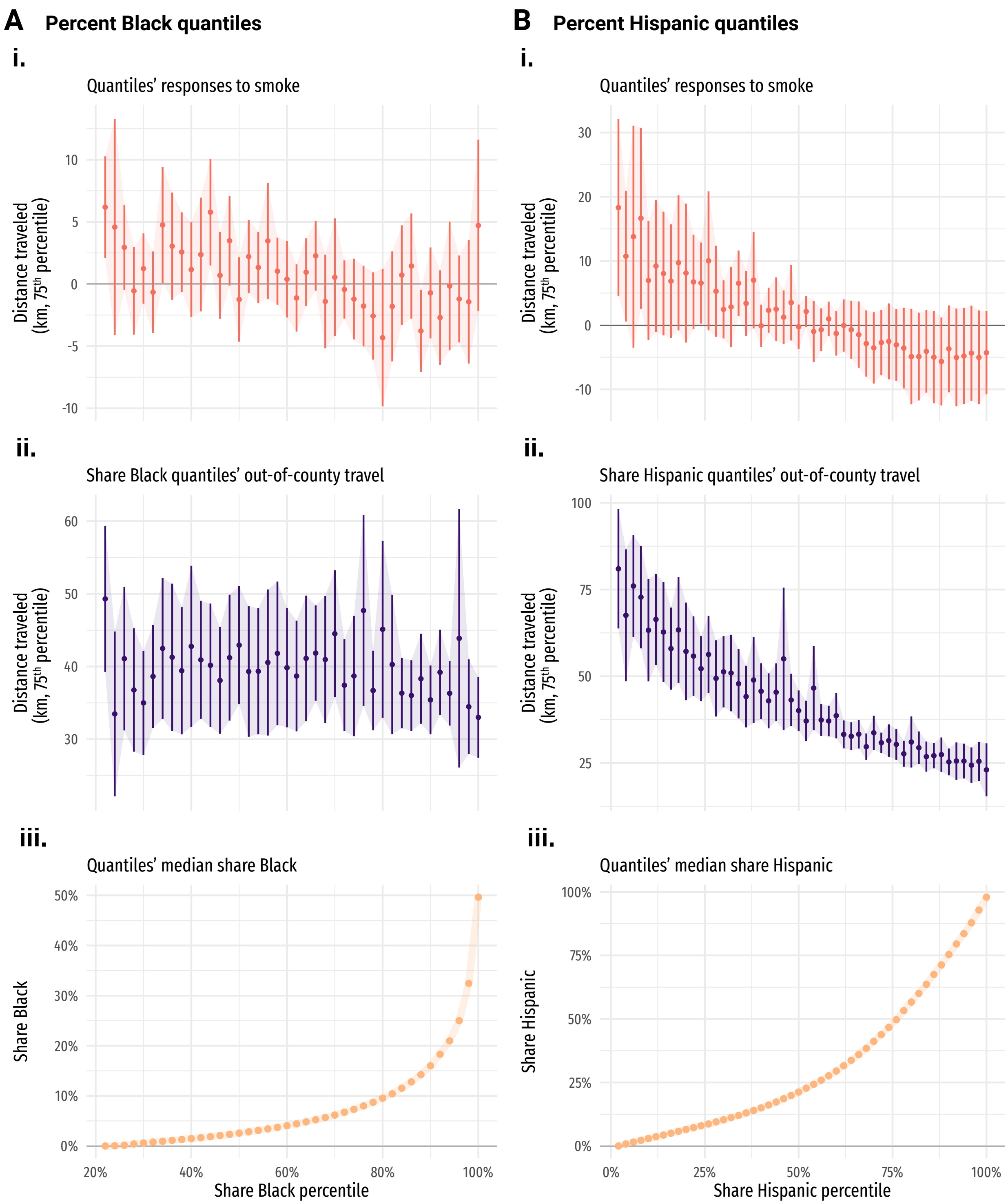
B Supplementary information

This file includes additional figures, tables, and details that support the main text.

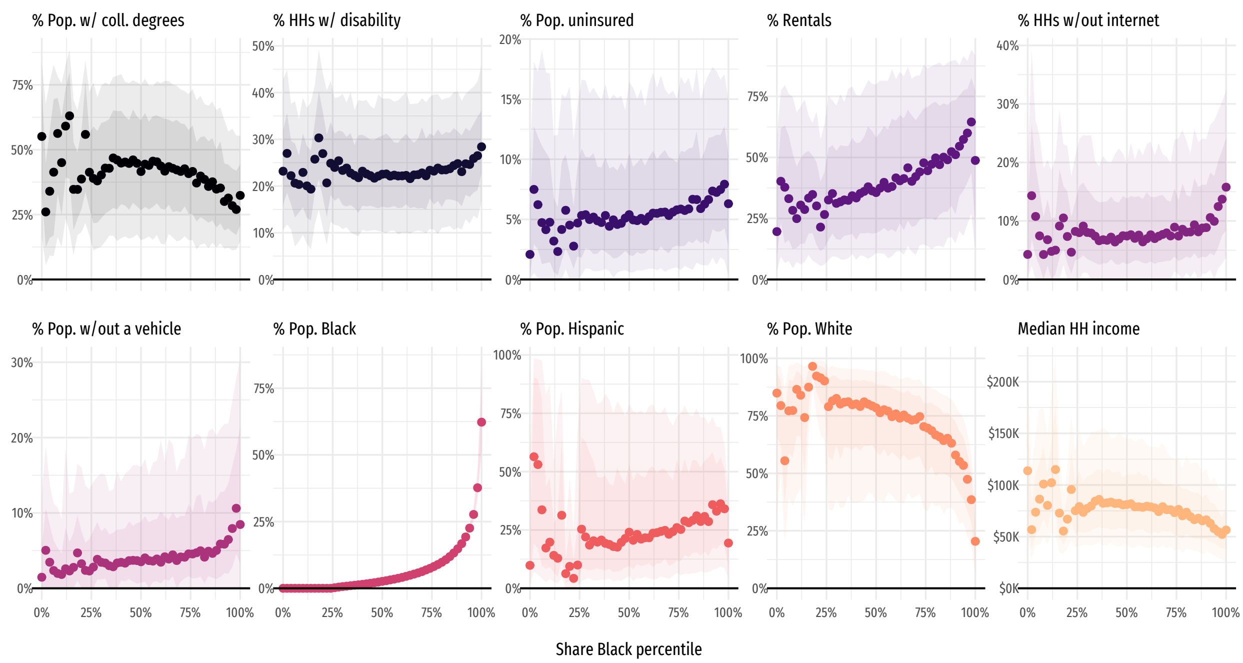
B.1 Supplementary figures



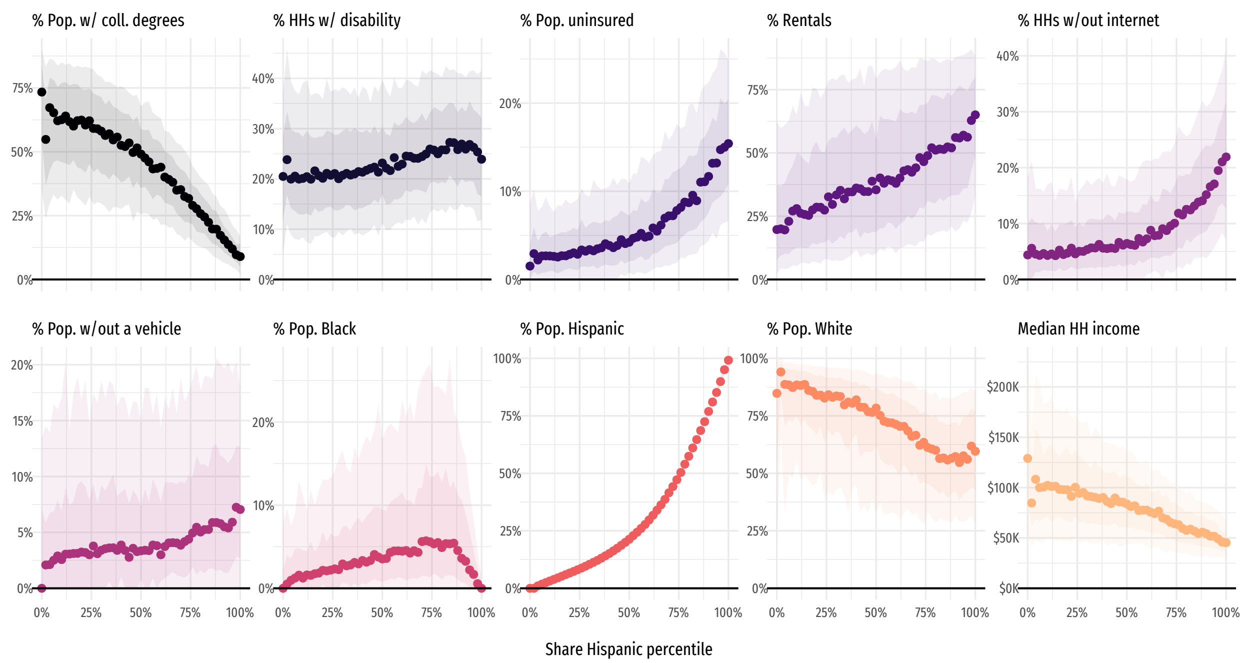
Supplementary Figure S2: Inequality in smoke-induced out-migration using the 75th percentile of distance traveled: Income and percent White. This figure reproduces Figure 2 but with CBGs' 75th percentile of distance traveled as the outcome variable.



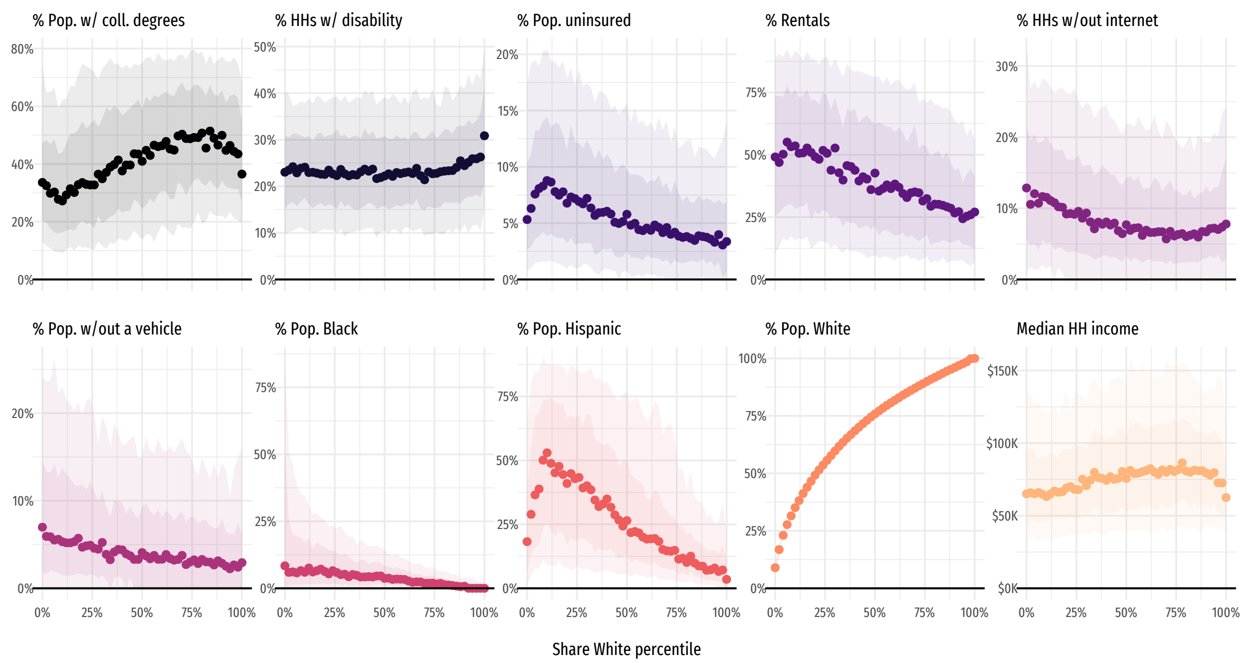
Supplementary Figure S3: Inequality in smoke-induced out-migration using the 75th percentile of distance traveled: Percent Black and percent Hispanic. This figure reproduces Figure 3 but with CBGs' 75th percentile of distance traveled as the outcome variable.



Supplementary Figure S4: Urban CBG percentile Black maps into many potential mechanisms among other socioeconomic dimensions. The figure reproduces Figure 4 but with Black population share rather than income. 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 (25th–75th percentiles) for the given bin. The lighter band marks the 10th–90th percentiles. Note that vertical axis scales change across subfigures to match variables' differing variation. Color denotes different variables.



Supplementary Figure S5: Urban CBG percentile Hispanic maps into many potential mechanisms among other socioeconomic dimensions. The figure reproduces Figure 4 but with Hispanic population share rather than income. 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.



Supplementary Figure S6: Urban CBG percentile White maps into many potential mechanisms among other socioeconomic dimensions. The figure reproduces Figure 4 but with White population share rather than income. 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 (25th–75th percentiles) for the given bin. The lighter band marks the 10th–90th percentiles. Note that vertical axis scales change across subfigures to match variables' differing variation. Color denotes different variables.

B.2 Supplementary tables

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%

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, *75th 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, *75th 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%

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

Supplementary Table S3: Robustness of regression results Including state by week-of-sample fixed effects

	(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	0.30^{**}	-0.40	0.55^{***}	0.82^{**}	0.05
	(0.12)	(0.29)	(0.16)	(0.35)	(0.20)
Any smoke $\times$ Het. percentile		1.4^{***}	-0.47^{**}	-0.93	0.55^{*}
		(0.50)	(0.21)	(0.61)	(0.29)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Panel B. *Dependent variable: 75^{th} percentile of distance traveled (km)*					
Any smoke	1.4	-7.0	5.9^{***}	13.2^{**}	-3.6^{*}
	(1.2)	(4.4)	(2.1)	(6.3)	(2.0)
Any smoke $\times$ Het. percentile		17.1^{**}	-8.3^{**}	-20.8^{*}	11.4^{***}
		(8.3)	(3.2)	(11.0)	(3.7)
N obs. (millions)	5.54	5.54	5.54	5.54	5.54
Fixed effects					
CBG	✓	✓	✓	✓	✓
State by Week-of-sample	✓	✓	✓	✓	✓

This table re-estimates the results in Table 1 but with state by week-of-sample fixed effects. Standard errors allow clustering within county and month-of-sample. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Supplementary Table S4: Lagged effects of smoke exposure Out-migration and smoke

	(1)	(2)	(3)	(4)	(5)
Panel A. *Dependent variable: Percent of visits outside of home county*					
Any smoke	0.28***	0.24***	0.22***	0.22***	0.21***
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
Lag of any smoke		0.26***	0.23***	0.21***	0.21***
		(0.09)	(0.08)	(0.07)	(0.07)
Lag_2 of any smoke			0.23**	0.20**	0.19**
			(0.10)	(0.08)	(0.07)
Lag_3 of any smoke				0.20*	0.18*
				(0.11)	(0.10)
Lag_4 of any smoke					0.14
					(0.11)
N obs. (millions)	5.54	5.52	5.49	5.46	5.44
R^2	0.73	0.73	0.73	0.73	0.73
Panel B. *Dependent variable: 75^{th} percentile of distance traveled (km)*					
Any smoke	1.5	1.4*	1.4*	1.4**	1.4**
	(0.89)	(0.74)	(0.70)	(0.69)	(0.69)
Lag of any smoke		0.87	0.90	0.93	0.94
		(1.3)	(1.1)	(1.1)	(1.1)
Lag_2 of any smoke			−0.17	−0.13	−0.07
			(1.4)	(1.2)	(1.1)
Lag_3 of any smoke				−0.22	−0.12
				(1.5)	(1.4)
Lag_4 of any smoke					−0.70
					(1.5)
N obs. (millions)	5.54	5.52	5.49	5.46	5.44
R^2	0.73	0.73	0.73	0.73	0.73
Fixed effects					
CBG	✓	✓	✓	✓	✓
Week of sample	✓	✓	✓	✓	✓
State by year	✓	✓	✓	✓	✓

This table estimates the lag structure of smoke exposure—*i.e.*, previous weeks' effects on contemporaneous out-migration. *E.g.*, Lag_3 represents the smoke indicator for three weeks prior. As in Table 1, Panel **A** estimates the effect of smoke exposure on the percent of POI visits that occur within visitors' home counties; Panel **B** estimates the effect of smoke exposure on the 75^{th} percentile of distance traveled to POIs. Each column in each panel represents a separate regression—using the same fixed-effect specification of CBG, week-of-sample, and state-year. Standard errors allow clustering within county and month-of-sample. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Supplementary Table S5: Robustness of regression results Decomposing *percent* of visits

	Number of visits		
	(1) Total	(2) In other counties	(3) In home county
Any smoke	-3.2	3.5^{*}	-6.7
	(4.9)	(1.9)	(4.4)
N obs. (millions)	5.54	5.54	5.54
Mean of dependent variable	521.0	115.1	406.0
Fixed effects			
CBG	✓	✓	✓
Week of sample	✓	✓	✓
State by year	✓	✓	✓

This table decomposes our outcome *percent of POI visits outside of home county*—*e.g.*, the results that Table 1 presents—into its parts: (1) the CBG's *total* number of POI visits (*i.e.*, the denominator); (2) the CBG's number of visits to POIs in *other* (non-home) counties (*i.e.*, the numerator), and (3) the CBG's number of visits to POIs in its county. Standard errors allow clustering within county and month-of-sample. Significance codes: ***: 0.01, **: 0.05, *: 0.1.

Supplementary Table S6: The right-tail of the distribution of distance-traveled appears to increase with smoke The effect of smoke on other quartiles of distance traveled

	Quartile of distance to visit		
	(1) 25^{th}	(2) 50^{th}	(3) 75^{th}
Any smoke	-0.025	-0.063	1.5
	(0.029)	(0.14)	(0.89)
N obs. (millions)	5.54	5.54	5.54
Fixed effects			
CBG	✓	✓	✓
Week of sample	✓	✓	✓
State by year	✓	✓	✓

This table's columns compares three outcome variables that each describe the distribution of a CBG's distance traveled for visits: (1) the 25^{th} percentile, (2) the 50^{th} percentile, and (3) the 75^{th} percentile. Column 3 represents one of the two out-migration measures used throughout the paper (Panel B in Table 1). Standard errors allow clustering within county and month-of-sample.

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

The following quote from SafeGraph's *Patterns* documentation[89] describes the company's approach to manipulating their aggregated data products so as to better protect individual privacy[114].

> 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$^{\text{th}}$ 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[5]. 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[115,116]. 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[72]. 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$^{\text{th}}$ 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.