Unequal avoidance: Disparities in smoke-induced out-migration

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Abstract

Organisms reduce risk exposure through short-term avoidance—*flight*. However, this flight strategy may not be equally accessible throughout a population. We combine cellphone movements, satellite-based wildfire smoke plumes, and Census data to document substantial heterogeneity/inequity in communities' tendencies to out-migrate to avoid smoke. Higher-income and whiter populations travel out of 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.

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1 Main

In the face of imminent danger, organisms often flee.[1] Yet nothing guarantees individuals have equal access to this strategy. Given recent work on inequality in the United States, one may suspect opportunities for avoidance are unequal: A substantial literature documents marked disparities along numerous dimensions—life expectancy and mortality, health, healthcare, pollution exposure, transportation, educational opportunities, and employment outcomes.[2] 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, existing inequities may worsen.

A contemporary case sheds light on this phenomenon. 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 enormous: between 2018–2021, wildfires cost more than $62 billion (Smith, 2022). In the same years, *every* Census Block Group on the West Coast faced wildfire smoke during at least 14 weeks (Figure 1). As wildfires ravaged larger and larger swaths of the US,[3] individuals increasingly confronted the choice to face fires' smoke or flee.

The literature documents the considerable health consequences of wildfire-smoke exposure (mortality, morbidity, and birth outcomes)—and the particulate matter associated with the wildfire smoke.[4] 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—shedding light on whether communities equally access avoidance strategies. For this analysis, we combine remotely sensed smoke plumes, cellphone-based movement data, and CBG-level demographic data for all recorded

[1] 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 (IPCC, 2022).

[2] Examples follow. **Life expectancy and mortality:** Harper et al. (2007), Chetty et al. (2016b), Currie and Schwandt (2016a), Alsan, Chandra, and Simon (2021), and Schwandt et al. (2021). Currie and Schwandt (2016b) provides a helpful overview. **Health:** Currie (2009), Almond and Chay (2006), and Aizer and Currie (2014). **Healthcare:** Chandra, Kakani, and Sacarny (2020), Dieleman et al. (2021), and Singh and Venkataramani (2022). **Transportation:** Chung, Myers, and Saunders (2001). **Education:** Bertocchi and Dimico (2012), Autor et al. (2019), Elder et al. (2021), and Blanden, Doepke, and Stuhler (2022). **Employment:** Chetty et al. (2014), Chetty et al. (2016a), Aneja and Xu (2021), Aneja and Avenancio-Leon (2022), and Davis and Mazumder (2022).

[3] Radeloff et al. (2005), Westerling et al. (2006), Radeloff et al. (2018), Baylis and Boomhower (2022), O'Dell et al. (2019), Burke et al. (2021), and Goss et al. (2020) document this phenomenon.

[4] O'Dell et al. (2019) and Burke et al. (2022) link wildfire smoke to $PM_{2.5}$. See (Richardson, Champ, and Loomis, 2012; Liu et al., 2017; Cascio, 2018; Kondo et al., 2019; Dedoussi et al., 2020; Heft-Neal et al., 2022; Kochi et al., 2012; Wen and Burke, 2022) for examples of the costs of smoke and/or $PM_{2.5}$ exposure.

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.

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 society's ability to respond to major risks/damages and suggest potentially fruitful avenues for policy.

Our results contribute to three strands of the literature: (1) environmental justice/inequality, (2) defensive investments and avoidance/adaptation, and (3) the economics of wildfires.

First, our results bring new insights into the burdens facing lower-income, Black, and Hispanic communities. A large environmental justice (EJ) and inequality literature has documented numerous dimensions along which historically marginalized communities face worse environmental quality—*e.g.*, in exposure to toxic-release facilities (Mohai and Saha, 2007; Bullard et al., 2008), air pollution (Hsiang, Oliva, and Walker, 2019; Colmer et al., 2020; Clark et al., 2022), and noise (Casey et al., 2017). Much of this literature focuses on documenting 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 may 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 documents and measures avoidance behaviors and defensive investments individuals employ against environmental risks. Avoidance strategies in this literature include consumption choices,[5] structural investments,[6] long-term migration,[7] and short-term travel.[8] Short-term travel and equity have received less attention—likely due to historical data limitations.[9,10] Our results help fill this gap—estimating the extent of short-term out-migration and its distribution across socioeconomic groups. Moretti and Neidell (2011) and

[5] *E.g.*, purchases of water bottles (Graff Zivin, Neidell, and Schlenker, 2011), pharmaceuticals (Deschênes, Greenstone, and Shapiro, 2017), masks (Sun, Kahn, and Zheng, 2017; Zhang and Mu, 2018), and air purifiers (Ito and Zhang, 2020)

[6] For example, Baylis and Boomhower (2021).

[7] For examples of long-term migration, see Boustan, Kahn, and Rhode (2012), Zheng and Kahn (2008), Bayer, Keohane, and Timmins (2009), Hornbeck and Naidu (2014), Tan Soo (2018), Freeman et al. (2019), Khanna et al. (2021), and Chen, Oliva, and Zhang (2022).

[8] For examples of short-term travel-based avoidance, see Neidell (2009), Graff Zivin and Neidell (2009), Richardson, Champ, and Loomis (2012), Chen et al. (2021), and Burke et al. (2022).

[9] Chen, Oliva, and Zhang, 2022 show younger, more-educated individuals are more likely to permanently migrate due to pollution. Sun, Kahn, and Zheng, 2017 find more affluent individuals are more likely to make defensive investments—masks.

[10] Our (short-run) migration results also relate to the climate-adaption literature—*e.g.*, Deschênes and Greenstone, 2011; Deschênes, 2014; Barreca et al., 2015; Barreca et al., 2016; Burke and Emerick, 2016; Massetti and Mendelsohn, 2018; Carleton et al., 2022; Lai et al., 2022.

Deschênes, Greenstone, and Shapiro (2017) both find 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. 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 economics of wildfires. Recent work raises equity concerns in the allocation of fire-fighting resources (Plantinga, Walsh, and Wibbenmeyer, 2022; Anderson, Plantinga, and Wibbenmeyer, 2022; Lennon, 2022), the incidence of wildfire hazard (Wibbenmeyer and Robertson, 2022), the incidence of fire suppression costs (Baylis and Boomhower, 2022), and the burden of wildfire smoke (Borgschulte, Molitor, and Zou, 2022). Limited previous work exists on avoidance behaviors in the setting of wildfires. In one exception, Richardson, Champ, and Loomis (2012) provide 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 Burke et al. (2022). Burke et al. show (1) individuals are aware of smoke exposure (via Google searches), (2) Google searches suggest individuals are seeking protection from smoke (*e.g.*, "air purifier" and "smoke mask"), (3) people are less happy when facing smoke (Twitter sentiment), and (4) smoke-based fine-particulate ($PM_{2.5}$) increases individuals' likelihood of remaining at home for the entire day. This fourth result from Burke et al. (2022) is closest to our central research question—whether out-migration to avoid smoke is equally accessed across socioeconomic groups.

While similar, our approach and results differ from Burke et al. (2022) on several important dimensions—complementing their analysis. Most notably, we document a strong relationship between out-migration and income; Burke et al. find little evidence that income correlates with communities' likelihoods of staying home.

These different conclusions likely stem from several differences in our empirical approaches. First, Burke et al. (2022) focus on counties, while our analysis focuses on Census Block Groups (CBGs). As we discuss below, the substantially higher spatial resolution afforded by CBGs allows a finer match between communities and incomes—resolving error from aggregation/the ecological fallacy (Anderton et al., 1994; Banzhaf, Ma, and Timmins, 2019). We also aggregate across days in a week rather than focusing on day-level outcomes as Burke et al. 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[11]—as found in Graff Zivin and Neidell (2009). 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

[11] *E.g.*, temporarily delaying visits to the zoo.

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. These differences in the unit of analysis and definitions of outcomes provide a complementary view of smoke-induced out-migration.

Together, our spatial disaggregation and temporal aggregation 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.

2 Data and descriptive statistics

For our analysis, we construct a panel that measures CBG-level weekly smoke exposure, out-migration, and demographics.

CBGs provide an ideal unit of analysis for several reasons. First, they are the smallest unit at which we can obtain cellphone-based movement data—our out-migration measure—and some socioeconomic data. Second, most CBGs delineate small geographic areas containing small populations (typically 600–3,000 individuals). Smaller areas help reduce aggregation-related errors when we assign smoke exposure, migratory behavior, and socioeconomic measurements to entire CBGs.

To maximize this 'match'—*i.e.*, to keep CBGs' areas small—we focus on urban CBGs—where urban population exceeds rural population. As Figure 1 illustrates, rural CBGs can be quite large (*e.g.*, southeastern Oregon), complicating smoke-exposure assignment. The panel of urban CBGs covers 27,555 in California, Oregon, and Washington through 2018-2021. These urban CBGs represent 91.3% of the US's west-coast CBGs, 93.3% of the population (47.1 million people), and 93.9% of visits (3 billion).[12]

2.1 Movement data

We measure communities' short-term migration patterns using SafeGraph's aggregated and anonymized cellphone-movement data (SafeGraph, 2022b). 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 Chen and Rohla, 2018) 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

[12] Tables A1 and A2 summarize the three datasets described below for *urban* west-coast CBGs and *all* west-coast CBGs—by CBG (Panel A) and by CBG-week (Panel B).

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 75$^{\text{th}}$ 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 A1) shows approximately 22% of POI visits occur outside individuals' home counties. Thus, the 75$^{\text{th}}$-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.[13]

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 (Valentino-Devries et al., 2018).[14] To address some privacy concerns, SafeGraph does not distribute microdata and applies differential-privacy techniques to many features of their aggregated data.[15] 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 (Squire, 2019a; Squire, 2019b). 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.

2.2 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 (NOAA, 2022). These publicly available data provide daily records of smoke-plume bound-

[13] Recent publications include Chen and Rohla (2018), Allcott et al. (2020), Chen et al. (2022), Dave et al. (2020), Jay et al. (2020), Long, Chen, and Rohla (2020), Weill et al. (2020), Bullinger, Carr, and Packham (2021), Fajgelbaum et al. (2021), Goolsbee and Syverson (2021), Ilin et al. (2021), Zhao, Holtz, and Aral (2021), Parolin and Lee (2021), Burke et al. (2022), Tai, Mehra, and Blumenstock (2022), and Glaeser, Gorback, and Redding (2022).

[14] Some prominent early critics of cellphone-based data later published work using cellphone-based data (see Thompson and Warzel, 2019 and later Thompson and Kelley, 2020).

[15] Appendix-section Privacy, noise, and censoring in SafeGraph Weekly Patterns data describes SafeGraph's differential-privacy approach and why it is unlikely to affect our results substantially.

aries across North America throughout the sample period.[16] 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 (Wen and Burke, 2021), numerous studies find communities' and individuals' HMS-based smoke exposure significantly correlate with human responses—*e.g.*, Miller, Molitor, and Zou (2017), Borgschulte, Molitor, and Zou (2022), Burke et al. (2022), and Heft-Neal et al. (2022).[17]

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.

2.3 Demographic data

Our data on CBGs' racial, ethnic, and income compositions come from the American Community Survey (ACS) 5-year estimates from 2019.[18] Specifically, for each CBG, we use the population counts of Black, Hispanic, and White individuals and each CBG's median household income. As discussed above, 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 (Manson et al., 2022).

3 Results

3.1 Empirical approach

Our goal is to estimate (1) the 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. As described above, we measure out-migration in two ways. First, we use the percentage of POI

[16] 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.

[17] We use historical data from the Wildland Fire Interagency Geospatial Services (WFIGS, 2022) to determine CBGs located near past wildfires.

[18] The appendix section Five-Year American Community Survey elaborates on this dataset.

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.[19]

Smoke_{iw} represents an indicator variable for whether CBG i encountered *any* smoke during week w.

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. find intergenerational mobility is linear in individuals' income percentiles; 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.

A causal interpretation of β—the effect of smoke on out-migration—requires that CBG i's smoke exposure in week w is independent of other determinants of i's movement in week w, conditional on the fixed effects. This requirement is plausible for several reasons. First, the FEs remove issues from seasonality (*e.g.*, summer vacation) and cross-sectional differences (*e.g.*, affluent, fire-prone areas), ruling out many potential confounds. Second, the sources of the smoke plumes (wildfires) are highly unpredictable in time and space (otherwise, they typically would not occur). Further, the smoke from these wildfires is carried toward or away from communities by erratic meteorological variation. Thus, for our identifying requirement to be violated, there must be a latent factor that (1) only appears when communities are downwind of wildfires—the result of unpredictable and semi-random processes—and (2) induces increased out-migration (but cannot be caused by smoke

[19] 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.

itself). Finally, event studies centered on communities' first smoke exposures of each calendar year (pooled across events and years) show sharp increases in out-migration beginning in the first week of smoke exposure (Figure B1). The event studies suggest increases in (A) the share of out-of-county visits, (B) the 75$^{\text{th}}$ percentile of distance traveled, and (C)the number of visits outside of individuals' home counties. Based upon this evidence and reasoning, we believe this identifying assumption is reasonably plausible.

3.2 Population-wide response to smoke

We first estimate Equation 1 without interactions/heterogeneity—identifying the average response to smoke exposure, pooled across all urban CBGs.

Column (1) of Table 1 demonstrates that, on average, communities 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 and week-of-sample.[20] 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 out-of-county POI visits by 0.28 percentage points. On average, approximately 22% of POI visits occur outside of residents' home counties (Table A1, 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 consistently travels away from their home counties when smoke plumes cover their homes. In the next section, we ask whether privilege-related demographics predict this behavior.

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 (Panel B of Table A1), 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 glossing over important differences in individuals' responses to wildfire smoke exposure. The following sections examine how out-migration behavior correlates with

[20] Table A3 reproduces the estimates in Table 1 but uses state by week-of-sample fixed effects. Table A4 drops CBGs affected by wildfires between 2018-2021. Results across the three tables are very similar.

income, race, and ethnicity.

3.3 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. Specifically, 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. For example, a CBG with median household income of \$74,000 is in the 50^{th} percentile and would have $\text{Percentile}_i = 0.50$.

Both outcomes (panels) in Table 1 reveal sizable and statistically significant relationships between communities' smoke-based out-migration behavior and income.

The direction of this heterogeneity follows a pattern similar to many relationships documented in the environmental- and social-justice literatures: more privileged communities display heightened avoidance behavior—here, out-migration—in the presence of wildfire smoke. In fact, for the lowest-income communities, there is no statistically significant evidence of out-migration. If anything, these communities reduce out-migration: the point estimates for percent out-of-county visits and distance traveled are both negative but do not differ significantly from zero. The level of out-migration only differs significantly from zero for communities above the 47^{th} percentile of income for out-of-county travel (panel A) and the 49^{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-county visits for the top percentile by 1.4 percentage points and increases their 75^{th} percentile of travel by 17.2 kilometers. Notably, the effects for the most affluent communities are 3–6 times larger than the pooled effects presented in Column (1). While there is little evidence that low-income communities travel to avoid smoke, Table 1 provides clear evidence that affluent communities exercise this strategy.

The empirical specification above imposes linearity in the relationship between CBGs' income percentiles and heterogeneous smoke-induced out-migration: an increase in one percentile increases out-migration by $\delta/100$. We relax this restriction by specifying Percentile_i as 50 mutually exclusive indicator variables. These indicators group neighboring percentiles together—*e.g.*, the first and second percentile are in the same indicator bin. 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.

Panel A of Figure 2 illustrates the results of this semi-parametric specification for income-based heterogeneity. Subfigure i shows the point estimates and their 95% confidence intervals for each of the 50 income-percentile bins' tendencies to out-migrate in response to smoke. Subfigure ii depicts bins' general tendencies to travel beyond their home counties (regardless of smoke). Finally, Subfigure iii maps each bins' median income.[21]

The results from this semi-parametric specification largely mirror those of the simpler regression in Table 1: A community's degree of smoke-based out-migration correlates strongly with the community's median income. Communities below the 50$^{\text{th}}$ percentile do not, on average, significantly out-migrate when facing smoke. While the increase in out-migration appears quite linear in communities' income percentile (the x axis), the tendency to out-migrate appears to increase sharply above the 90$^{\text{th}}$ percentile—approximately the same point at which the income distribution sharply increases. Finally, the point estimates of this semi-parametric estimation (depicted Figure 2Ai) suggest an even higher rate of smoke-induced out-migration (~1.4 percent) relative to the results from the linear-specification results in Table 1.

Subfigure Aii highlights notable differences in other-county travel throughout the income distribution. The same communities that are more likely to out-migrate in the presence of smoke are already traveling more. These insights are also corroborated by our distance-traveled measure (see Appendix Figure B2A).

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. There is no significant evidence that smoke induces any out-migration in communities below the 30$^{\text{th}}$ percentile of income.

3.4 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 our specification of income-based heterogeneity, we estimate Equation 1 with Percentile_i defined as CBG i's percentile (between 0 and 1) in the West Coast's distribution of the share of the population that is Black (Column 3), Hispanic (Column 4), or White (Column 5).

Table 1 provides more evidence that historical privilege[22] 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.*, their confidence intervals include zero).

[21] Appendix Figure B2A reproduces Figure 2A with distance traveled as the outcome.

[22] *I.e.*, populations that are less Black, less Hispanic, and/or more White.

The story is similar for 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 75th percentile by 11.5 kilometers). As we found with the most-Black communities, the West Coast's most-Hispanic communities show no significant evidence of smoke-induced out-migration. Communities whose population is at least 24-percent Hispanic (the 54th 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 historical privilege: communities with larger shares of White individuals out-migrate more than less-White communities. The least-White communities (less than 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. The most-White urban communities on the West Coast (~100% White) out-migrate significantly more than less-White communities. Communities above the 41st percentile of share White (communities that are at least 69% White) all show statistically significant evidence of smoke-induced out-migration.

As with income-based heterogeneity, we estimate a less-parametric model of heterogeneous out-migration for CBGs' percentiles of their population shares of Black, Hispanic, or White individuals. Panel 3A and Panel 3B display the results of these semi-parametric specifications for share Black and share Hispanic. Panel 2B illustrates the results for share White.[23]

The semi-parametric specification yields similar conclusions to the linear specification: out-migration behavior strongly correlates with less-Black, less-Hispanic, and more-White populations. At approximately the same point in the distribution that communities become majority White (the 25th percentile, see Panel 2B), they also significantly out-migrate when faced with smoke. As these majority-White CBGs increase in their percentage of White inhabitants, their smoke-induced out-migration continues to increase. Conversely, when the share of Hispanic individuals in a CBG crosses fifty percent (*i.e.*, majority-Hispanic, ~75th percentile, see Panel 3B), out-migration is approximately zero—and drops below zero as the share Hispanic increases. Very few CBGs on the West Coast have a majority-Black population—80 percent of urban west-coast CBGs are less than 10 percent Black. Even with this low representation, Panel 3A still illustrates a clear trend: communities with larger Black-population shares out-migrate significantly less when facing smoke, relative to less-Black CBGs.

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, they travel out-of-county substantially less. The trend in communities' Hispanic population is particularly evident. Twenty-five percent of POI visits in the least-Hispanic communities occur

[23] Appendix Figures B3A, B3B, and B2B repeat these figures for the 75th percentile of distance traveled.

outside individuals' home counties; this number drops below twelve percent for the most-Hispanic communities.

3.5 Interpreting out-migration behavior

Above, we observe evidence that the share of non-home-county visits increases 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, an increase in the denominator (the total number of visits) could cause this ratio to increase—even when the number of other-county visits did not increase. However, an event study for the number of other-county visits (Appendix Figure B1C) suggests that the numerator—the *number* of other-county visits—increases due to smoke exposure. Further, when we estimate percentile-level effects of smoke exposure on the number of visits to non-home counties (rather than the share), the point estimates are positive for communities above the median income (Figure B4). Smoke exposure increases the *level* of out-migration in affluent communities. Consequently, even if the total number of trips (the denominator) declines,[24] the level of out-migration appears to increase in above-median-income communities in response to smoke. The results in the previous subsections can be interpreted as describing the effects of wildfire smoke on communities' levels and shares of out-migration.

4 Discussion and conclusion

Notably, the dimensions along which we document heterogeneous out-migration are descriptive. Our empirical strategy 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 different dimensions, Figure 4 reinforces how strongly income correlates with many variables important for equity, policy, and understanding potential mechanisms.

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*

[24] Burke et al., 2022's find that smoke induces more households to remain at home. Figure B4 suggests a small reduction in total visits.

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.[25] 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 (Colmer et al., 2020) 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 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.

While populations often face common hazards, individuals do not equally employ avoidance strategies. We find robust and significant evidence that *some* communities out-migrate in the presence of smoke; other communities show little evidence of out-migration. Our results show avoidance strongly correlates with income, race, and ethnicity—salient dimensions for contemporary and historical disadvantage. Without additional policies or interventions, unequal access to avoidance may exacerbate existing inequality—a potentially important insight as humanity faces a rapidly changing climate.

[25] For examples, see Miller, Molitor, and Zou (2017) and Borgschulte, Molitor, and Zou (2022).

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5 Tables

Table 1: Regression results Out-migration responses to smoke and distribution

		Percentile-based heterogeneity			
	(1)	(2) HH Income	(3) % Black	(4) % Hispanic	(5) % White
Panel A *Dependent variable: Percent of POIs 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
R^2	0.73	0.73	0.73	0.73	0.73
Panel B *Dependent variable: 75th percentile of distance traveled to POIs (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
R^2	0.079	0.079	0.079	0.079	0.079
Fixed effects					
CBG	✓	✓	✓	✓	✓
Week of sample	✓	✓	✓	✓	✓

Notes: 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 A3 reproduces the current table with *state by week-of-sample* fixed effects. Standard errors allow clustering within county and month-of-year (*e.g.*, January). Significance codes: ***: 0.01, **: 0.05, *: 0.1.

6 Figures

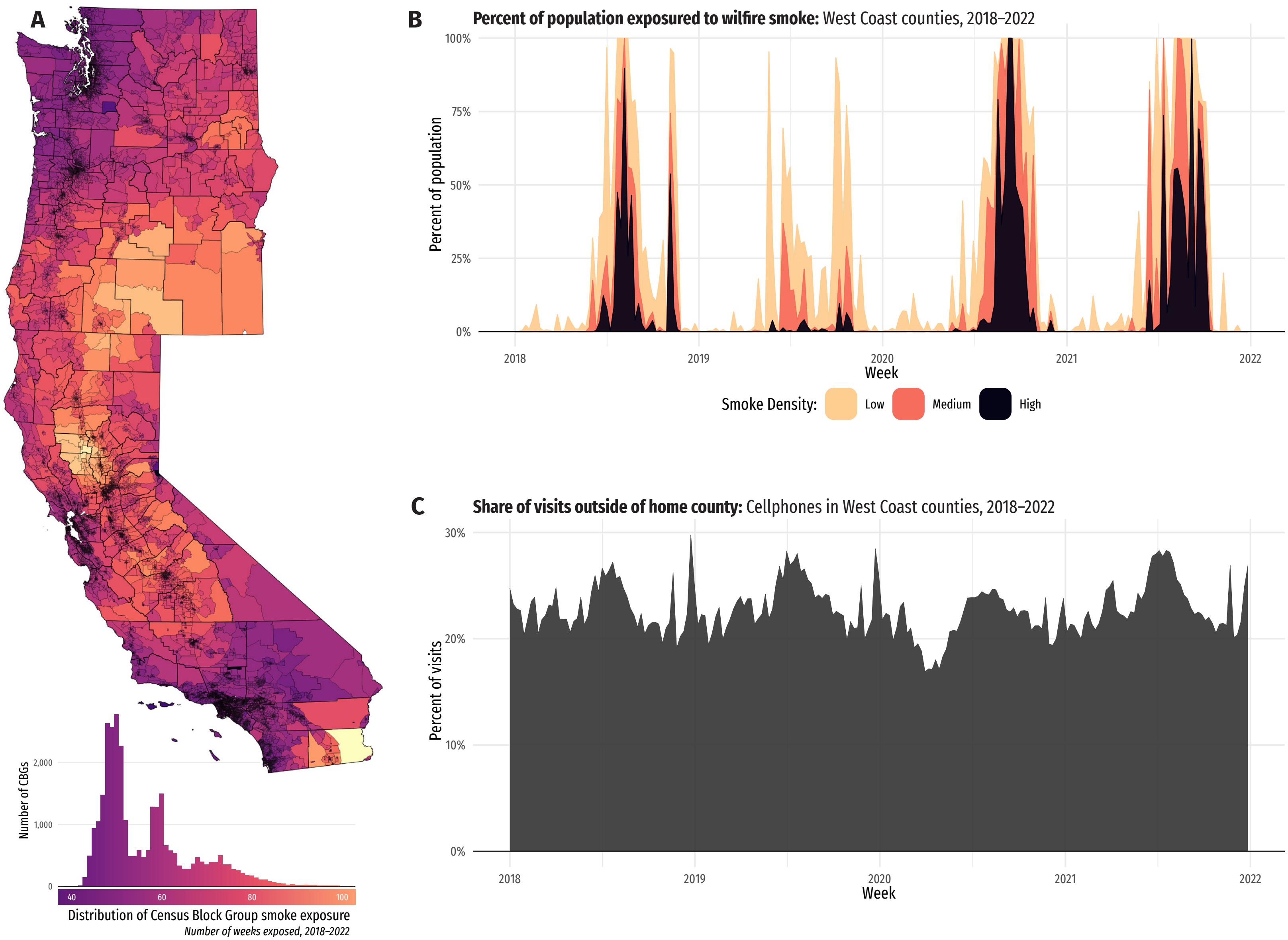

Figure 1: Smoke exposure and mobility. Panel **A** illustrates the study area—the West Coast of the United States. The smallest features in the map in **A** are shaded in proportion to the number of weeks that Census Block Groups (CBGs) encountered wildfire smoke 2018–2021. Panel **B** depicts the share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

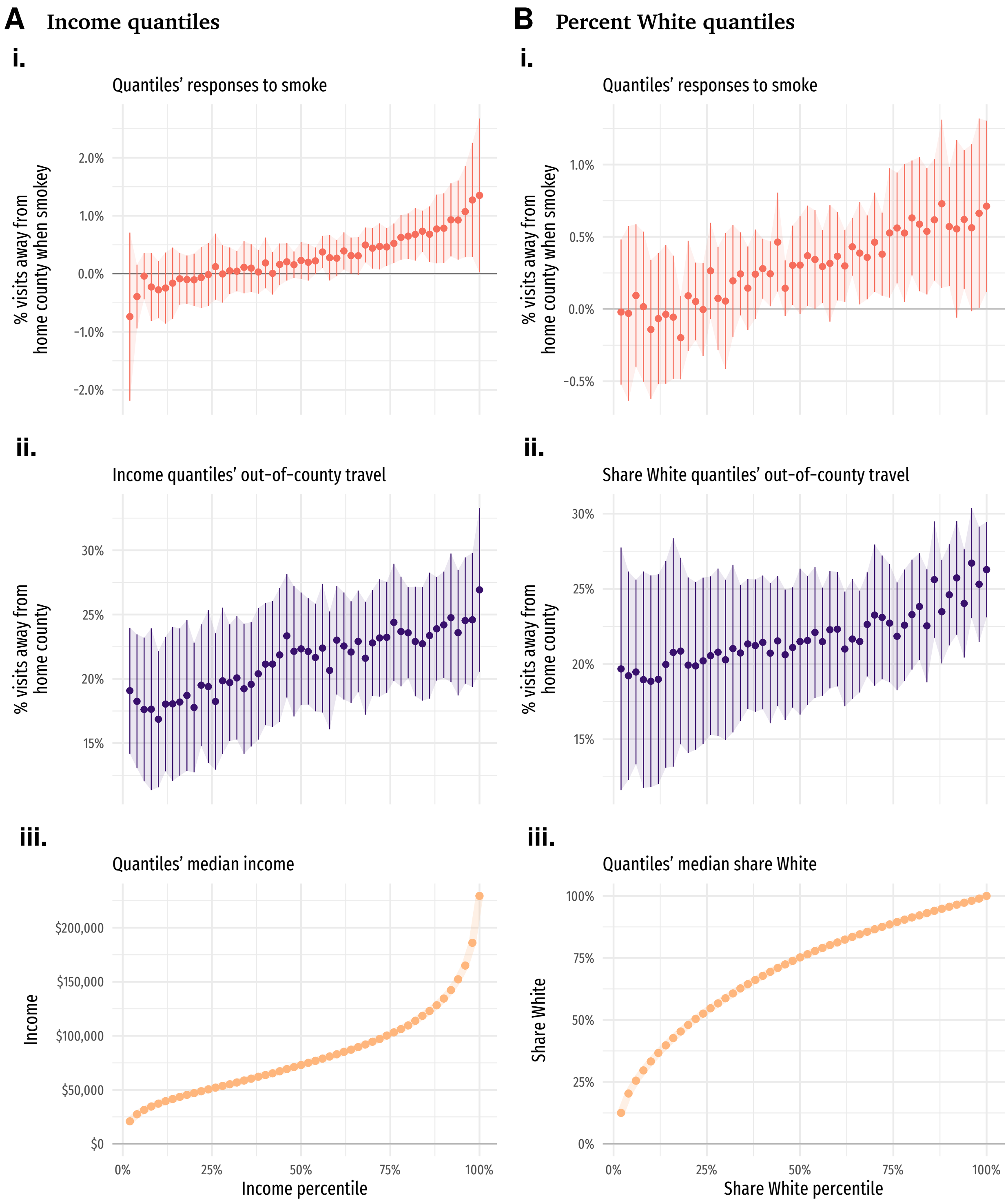

Figure 2: Inequality in smoke-induced out-migration: Income and percent White

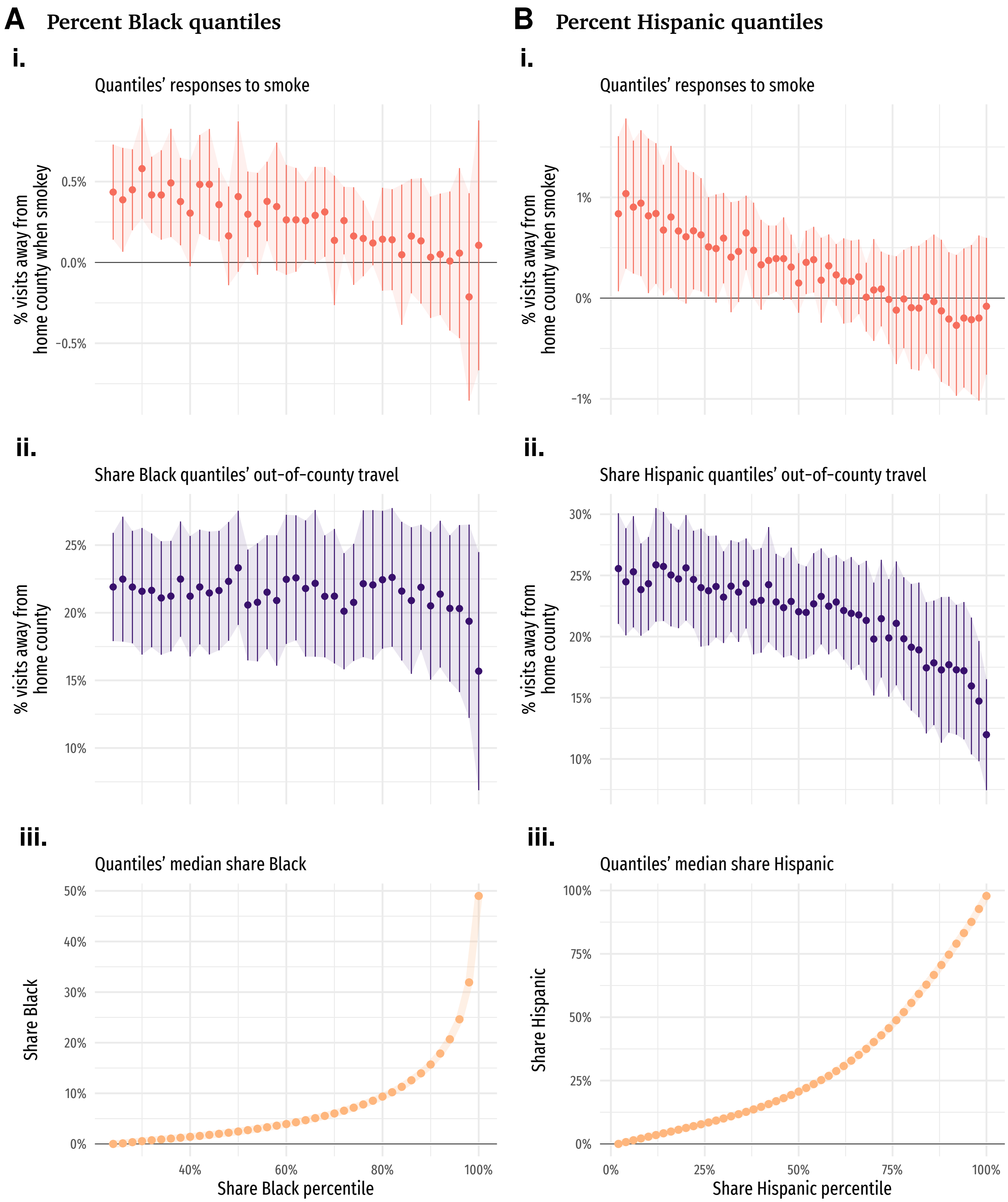

Figure 3: Inequality in smoke-induced out-migration: Percent Black and percent Hispanic

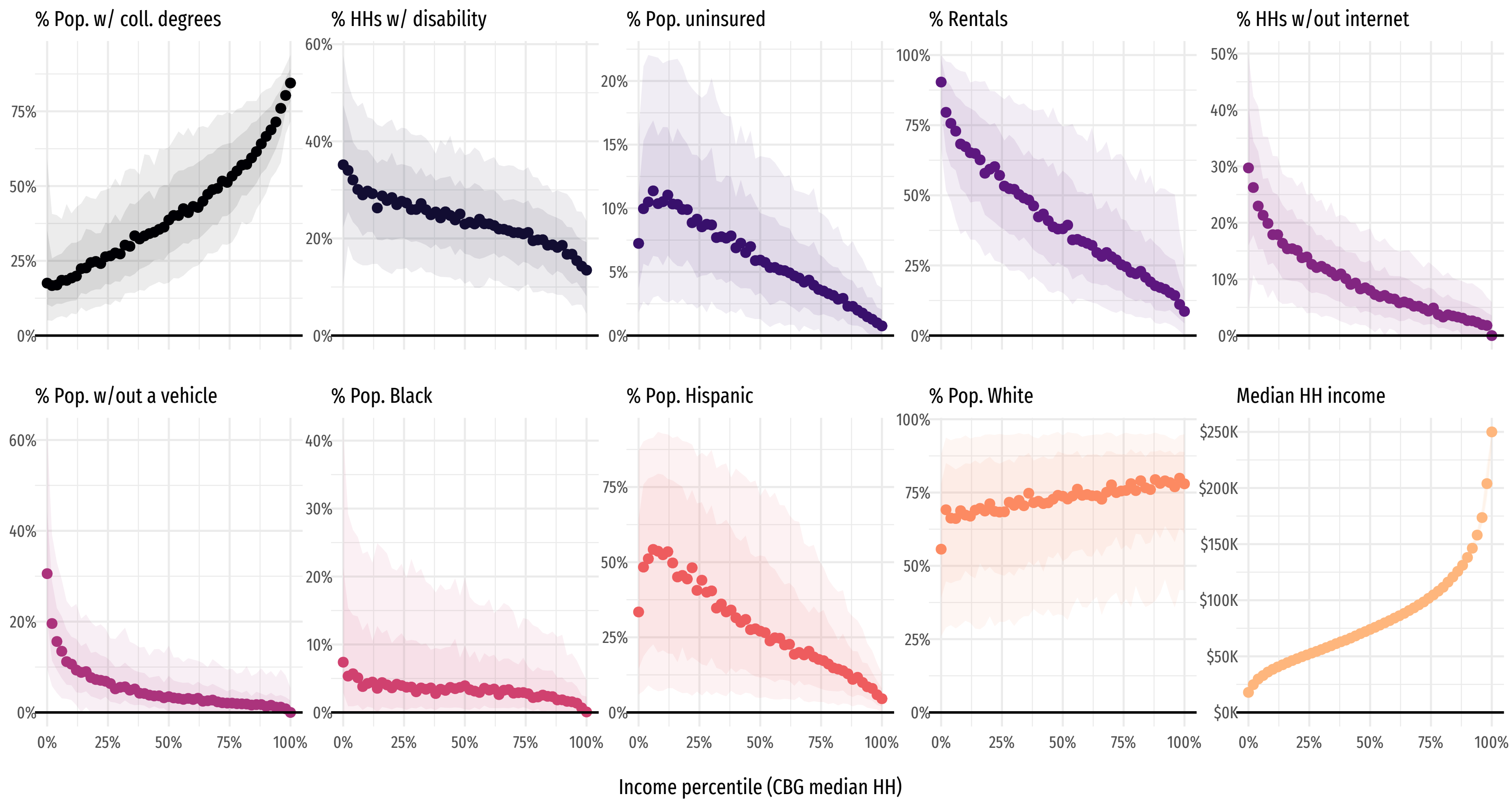

Figure 4: Urban CBG income percentiles and other socioeconomic dimensions Each subfigure summarizes urban, west-coast CBGs levels of the given variable by two-percentile bins (*e.g.*, combining the first and second percentiles). Solid dots the median. The first, darker band gives the interquartile range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

Appendix A Tables

Table A1: 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 A2 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. The Data and descriptive statistics section describes variables and sources. The *Smoke* variables in Panel B summarize indicators, so we omit the percentile summaries.

Table A2: 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%

Notes: This table exands the summaries of Table A1 to all CBGs (rather than restricting to urban CBGs).

Table A3: Robustness of regression results Adding state interaction of fixed effects

	(1)	*Percentile-based heterogeneity* (2) HH Income	(3) % Black	(4) % Hispanic	(5) % 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
R^2	0.73	0.73	0.73	0.73	0.73
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
R^2	0.081	0.081	0.081	0.081	0.081
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.

Table A4: Robustness of regression results Dropping CBGs directly affected by wildfires

		Percentile-based heterogeneity			
	(1)	(2) HH Income	(3) % Black	(4) % Hispanic	(5) % 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
R^2	0.73	0.73	0.73	0.73	0.73
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
R^2	0.078	0.079	0.079	0.079	0.079
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).

Appendix B Figures

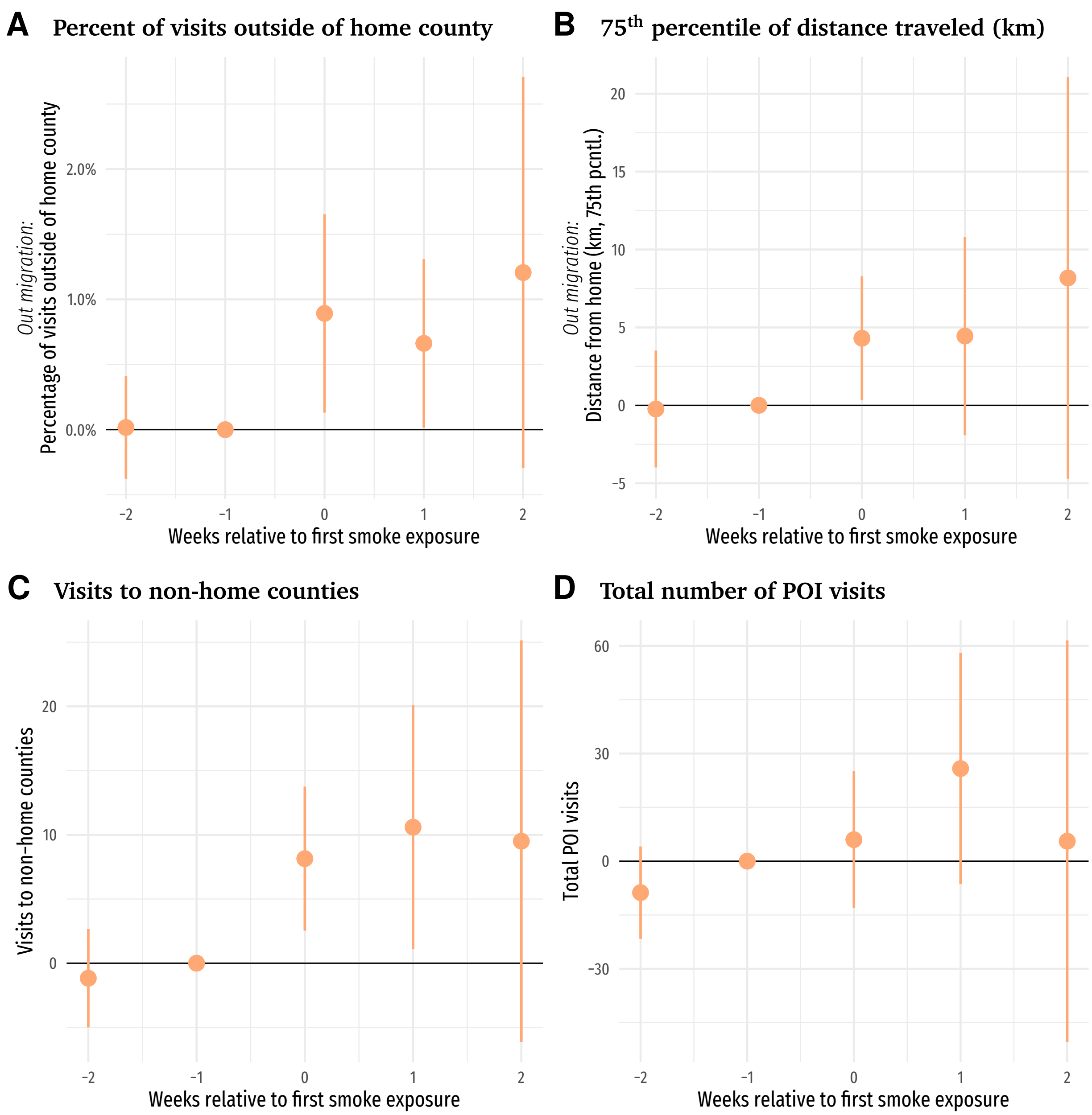

Figure B1: Event studies of smoke exposure. Each event study is centered on the first week that CBGs encounter smoke for each calendar year (excluding 2021). The regression includes a fixed effect for the week the smoke started, county-month (of calendar), and county-year. We cluster the standard errors by county and month. Panels (a)–(d) only differ in their outcome variable: (a) CBG residents' shares of visits beyond their home counties, (b) CBGs' 75$^{\text{th}}$ percentiles of distance traveled in the week, (c) the number of visits to POIs in non-home counties, and (d) the total number of POI visits. Panel (a)'s outcome is the outcome in (c) divided by the outcome in (d).

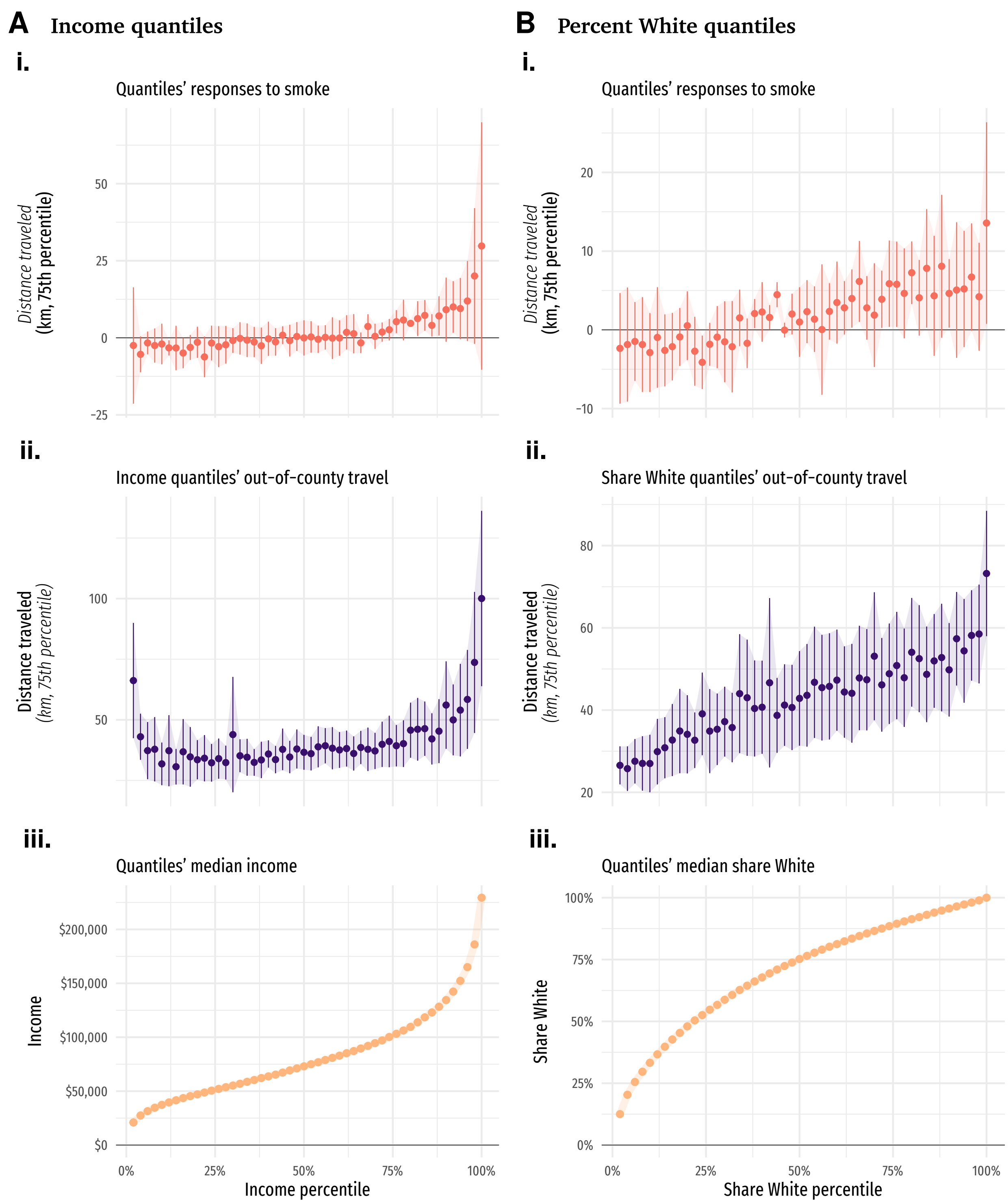

Figure B2: Unequal smoke-induced traveled: By income and percent White

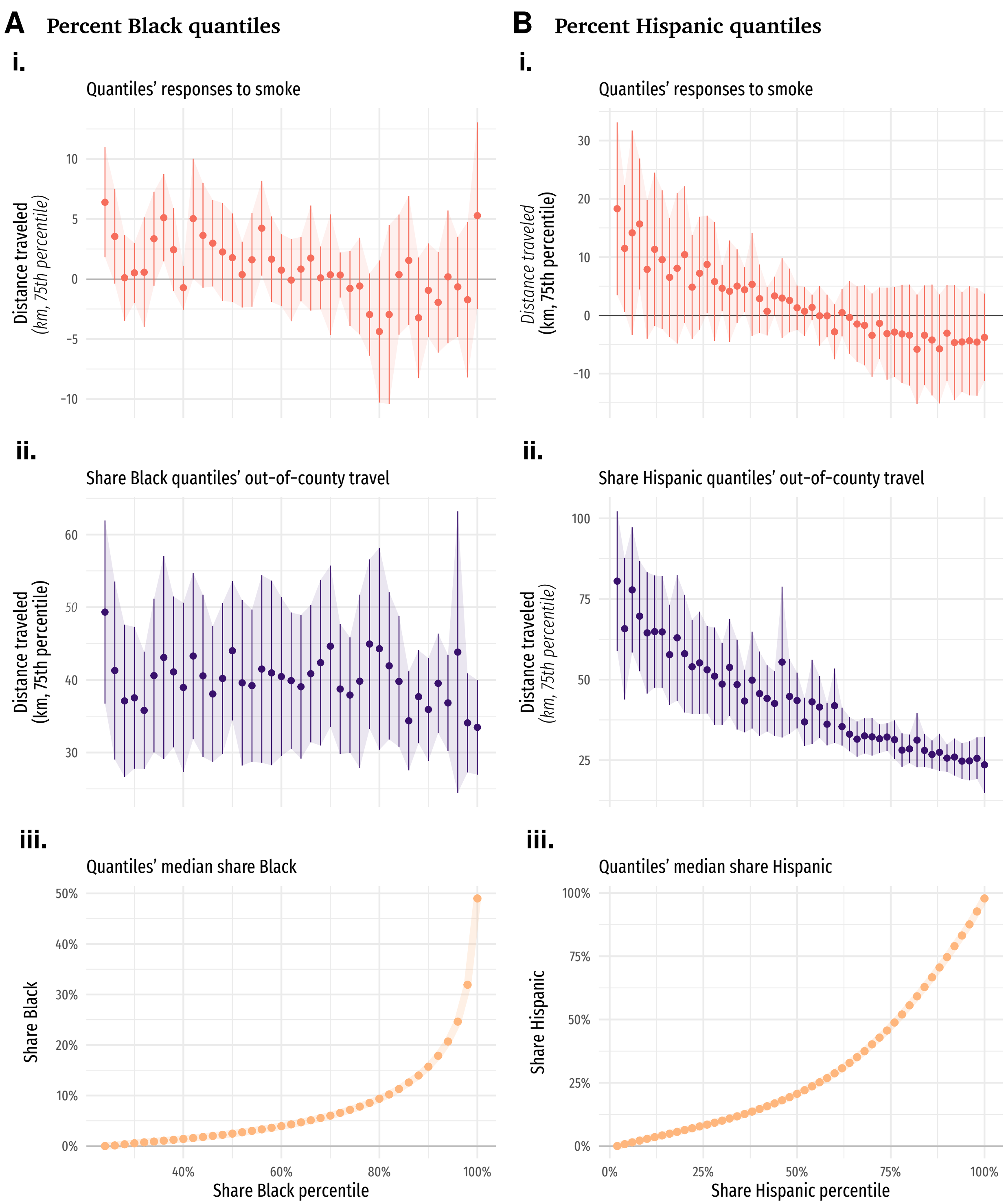

Figure B3: Unequal smoke-induced traveled: By percent Black and percent Hispanic

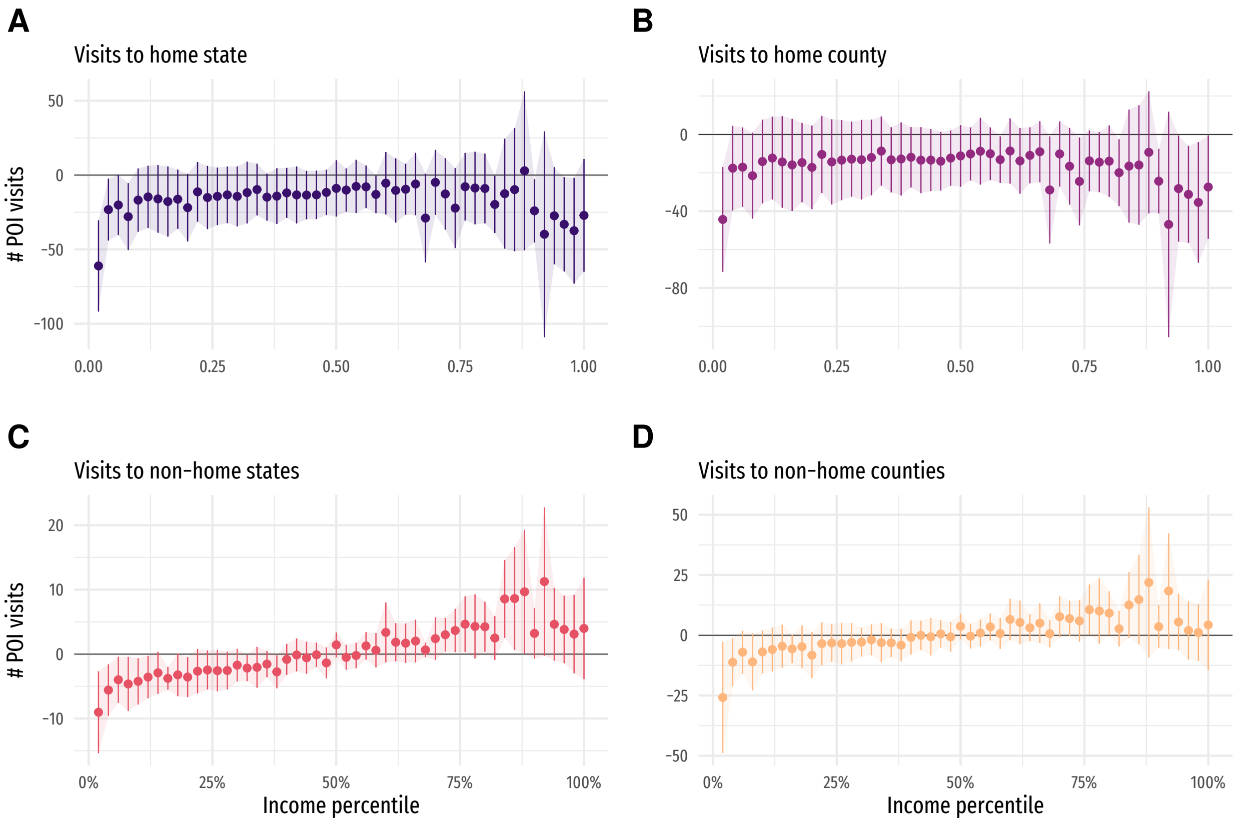

Figure B4: Smoke exposure's effect on number of visits to home and non-home counties/states This figure estimates smoke exposure's impact on the *level* of visits (the count)—rather than the percentage—across income percentiles (grouped into two-percentile bins). Panel **A** shows the effect of smoke exposure on the number of visits to residents' home **states**; Panel **B** shows the effect of smoke exposure on the number of visits to residents' home **counties**. Panels **C** and **D** show the effect of smoke exposure on visits to other states (**C**) and counties (**D**).

Appendix C Data

C.1 Privacy, noise, and censoring in SafeGraph Weekly Patterns data

The following quote from SafeGraph's *Patterns* documentation SafeGraph, 2022b describes the company's approach to manipulating their aggregated data products so as to better protect individual privacy SafeGraph, 2022a.

> 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 Movement data, 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).

C.2 Five-Year American Community Survey

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 A1 and A2).