

# Unequal Adaptation: Socioeconomic Stratification in Short-Term Mobility Responses to Wildfire Hazards in Spain

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## Abstract

Wildfires pose hazards for humans through fire proximity and smoke exposure, and are expected to pose increasing risks due to climate change. Existing literature has not extensively inquired how wildfires affect short-term mobility as an adaptive response to these events. We use digital trace mobility data from the Spanish Ministry of Transportation to examine how proximity to wildfires and consequent air pollution due to wildfires affect short-term mobility in mainland Spain from 2022 to 2024. Additionally, we examine the differing impact of wildfires on mobility by the intensity of exposure and leverage district level income data provided by the Spanish Statistical Institute (INE) to inquire about stratified responses. We find evidence for wildfire related short-term displacement uniquely among the upper quartile of income at the district level, and that this displacement is also visible at less acute exposure levels. Similarly, we observe that exposure to wildfire-related PM 2.5 is associated with short-term displacement only among upper quartile income districts. Our findings highlight the relevance in existing spatial and socioeconomic inequalities in shaping adaptive capacity to environmental hazards.

## Introduction

Wildfire seasons are becoming longer and more severe in association with climate change (Jolly et al. 2015; Richardson et al. 2025). Wildfires also pose serious economic, social, and health risks to affected populations (Wang et al. 2021; Romanello et al. 2025). Such risks emerge from wildfires as a dual hazard, involving both proximity to the destructive force of an active fire, and exposure to wildfire related particulate matter (Mani et al. 2024; Aguilera et al. 2021). While research on climate-related migration is relatively well developed, less is known about short-term mobility as an adaptive response to sudden and severe climate risks, such as wildfires, due largely to data limitations in capturing short-term, predominantly internal movements that unfold over days. Though much of past research utilized survey data and census records to study longer term migration trends of static populations, more recent availability of digital trace data has allowed studying the dynamic movement of population in response to external hazards that can affect the habitability of a physical environment (Huang et al., 2025; Gilmore et al., 2024).

In this study, we use similar digital trace data to examine to what extent both proximity to wildfires and exposure to wildfire-related particulate matter smaller than 2.5 micrometers (PM 2.5) shape short-term mobility in mainland Spain from 2022 to 2024. Spain represents a valuable case as it has experienced some of the worst fire seasons on record in recent years in Europe, and trends involving earlier starts to the fire season threaten to exacerbate wildfire exposure. Following the theoretical foundations of the aspirations and capability framework (de Haas, 2021), we address the following questions in this paper: First, *how does proximity to wildfires change short-term residential displacement?* Second, *how does exposure to wildfire particulate matter change short-term residential displacement?* Third, *to what extent do these outcomes vary by district-level income?* While prior studies in the broader wildfire-mobility literature focus on a single wildfire or disaster event, we add to the literature by expanding our analysis to several large wildfires that occurred in Spain over a span of two years.

We integrate data from several sources. First, our key outcome variable comes from anonymized mobile phone-based mobility data from the Ministry of Transport, Mobility and Urban Agenda of Spain (MITMA) (2024). This data contains roughly 20% of the Spanish population, and is post-stratified by gender, age, and income to achieve national representativity. From this data, we are able to construct a measure of *short-term residential displacement* by comparing the number of residents of a given district present within that district on a given day (overnight stays), compared to the reported census population of that given district. In doing so, we bridge a gap between existing wildfire-related mobility research, which typically describes changes in short-term mobility patterns (not specifically displacement), and climate migration research, which is more focused on long-term displacement. We then consider proximity to wildfire based on data from the European Forest Fire Information System (EFFIS), which in turn is based on imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Sentinel-2, gridded wildfire related particulate matter data produced by Hänninen et al. (2022), and district level income data produced by the Instituto Nacional de Estadística (INE - Spanish Statistical Institute). Upon this combined data, we apply two-way fixed effects regression models to exploit spatial and temporal variation in wildfire appearances towards the following research questions. We find that at close proximity to wildfire boundaries, the highest degree of residential displacement is observed

among the wealthiest districts in our sample. Concerning exposure to wildfire particulate matter, we find little changes in residential displacement across the first three district income quartiles, with only the fourth district income quartile containing increases in residential displacement.

## Background

As global temperatures increase, the frequency and intensity of climate-related disasters are increasing, leaving large populations vulnerable to risks from direct and indirect effects of these events (IPCC 2023). Many parts of the world, such as western USA and southern Europe, have been experiencing longer, hotter, and drier summer months that provide weather conditions favorable to vegetation fires and longer fire seasons (Halofsky et al 2020; Jolly et al 2020; Dupuy 2020). While fires are an important part of a natural ecosystem, they can cause harm to individuals and communities in close proximity through increased risk of morbidity and fatality, loss of property, and psychological impacts from experiencing traumatic events (Reid et al 2016; Liu et al 2015; Belleville et al 2019; Beaglehole et al 2018; To et al 2021; Syphard et al 2012).

In 2022, parts of Europe, the Middle East, and North Africa were impacted by some of the worst fires in recent history (JRC, 2023; San-Miguel-Ayanz et al., 2023). The region experienced multiple heatwaves and low amounts of rainfall all year, contributing to weather conditions conducive to forest fires (Xu et al., 2024). Spain was one of the worst affected countries, with exceptionally low rainfall as well as the hottest average temperature since 1961, (San-Miguel-Ayanz et al., 2023). These weather conditions resulted in the largest burnt area in the region at —267,947 ha—, which represented the highest spike in burnt area in the country since 1994 (San-Miguel-Ayanz et al., 2023). Overall, the size and the frequency of fires in Spain has been increasing over the past four decades, with large wildfires being the most important disruptive agents of forest expansion (Castellnou et al., 2007), and increasing risks associated with exposure (Aguilera et al., 2021; Finlay et al., 2012).. In a more recent study, Torres-Vázquez et al., (2026) find a sharp increase in human exposure to wildfire in Catalonia, Spain, particularly related to urbanization trends in fire-prone areas.

In recent research, scholars have considered how and to what extent short-term mobility can be used as an adaptation strategy to climatic changes (de Sherbinin 2022; Garip & Reed 2025; de Haas 2021; McLeman and Smit 2021). Such work has drawn attention to mobility patterns related to wildfires in various parts of the world. We add to the literature by focusing on Spain which has largely not been a geographical focus in this area of research. With wildfire seasons becoming longer and hotter in Spain, we focus on understanding mobility behaviors as an adaptation strategy of people residing in areas in close proximity to large wildfires in the country between 2022-2024. While migration often encompasses moves that are often long-term or permanent, climate-related mobility is a relatively short-term response to disasters and often observed in the form of evacuation. Spain uses the Emergency Warning Satellite Service (EENA, 2020) to send

push notifications to cellphones in disaster affected areas to alert them and provide necessary guidance. While open-source news articles suggest evacuation orders are often mandatory, we find limited infrastructure for policy frameworks for protection of people from wildfires and wildfire-related air pollution. Until recently, studies utilized rich survey data to observe migration or mobility patterns, as in the well-known case of Hurricane Katrina in New Orleans in 2005 (Fussell et al., 2010; Elliot and Pais 2006), while others conducted computerized simulations such as using agent-based models (Entwistle et al., 2016; Entwistle et al 2020; Kniveton et al 2011). More recently, studies have leveraged high resolution mobility data that provides high spatial and temporal granularity particularly relevant for mobility patterns. In particular, scholars have leveraged location and cellphone data to study short-term population movement as a response to disasters (Lu et al 2016; Bengtsson et al 2011; Nyhan et al 2019 ; Yabe et al 2019; Yabe et al 2022). Given that high resolution data provides greater opportunity for more precise analyses, we build on the small but growing literature using cellphone data to study the effects of wildfires in Spain on short-term residential displacement as an adaptation response.

Wildfires could have unequal impacts on communities and be especially consequential where there is a lack of sufficient and appropriate capabilities to adapt to and cope with a natural disaster (Chas- Amil et al 2022; Paveglio et al 2018; Lambrou 2023; Fekete et al 2023). Some studies use mobile data to focus on socioeconomic differences in the timing of mobility to understand whether adaptation patterns vary. For example, the devastating wildfire in Valparaiso, Chile in 2024 led the local government to issue public warnings through Short Message Service (SMS) notifications to the affected populations. Elejalde et al (2025) find a strong association between the receipt of SMS alerts and subsequent evacuation, with lower income groups evacuating more slowly and returning later than higher income groups. Similarly, Nausharinove et al (2025) also find evidence of socioeconomic stratification in patterns of evacuation-related movement after the fire in Chile, with the lowest socioeconomic group returning the latest. In a similar vein, Wu et al (2022) overlay GPS data from mobile devices with socio-demographic and built environment data to study evacuation rates during the 2019 Kincade Fire in Sonoma County, California. The study finds strong associations of likelihood of evacuation rates from aggregated census blocks, with higher likelihood where educational attainment and median ages are higher compared to blocks with lower educational attainment and younger ages. Similar socioeconomic disparities have been found for other disasters, such as Deng et al. (2021) find a strong association between race and wealth and the likelihood of evacuation after Hurricane Harvey in the United States in 2017, with disadvantaged populations less likely to evacuate.

Besides direct effects of wildfires by proximity, evidence suggests that air pollution from wildfire smoke can significantly impact air quality and presents specific health risks (Burke et al., 2023). While wildfire events often lead to state action in the form of public warnings and evacuation orders, governments rarely have policies in place for intervening for smoke-related hazards, leaving affected populations to rely primarily on their own knowledge and resources, and thereby increasing exposure to vulnerable populations. An extensive literature documents the negative effects of wildfires from proximity and from exposure to wildfire-related PM<sub>2.5</sub> on outcomes

related to morbidity and mortality, including burns, injuries, respiratory illnesses, and death (Xu et al 2020; Mani et al 2024; Cascio et al 2017; Chen et al 2021; Finlay et al 2012). However, there has been less focus on the effects of wildfire smoke and related PM2.5 exposure on adaptation strategies in general, and more specifically, on mobility patterns.

Within this relatively new area of research and growing literature, Burke et al. (2022) find increased exposure to wildfire-related PM2.5 in the U.S. leads to multiple behavioral responses, including an increase in online search terms related to air quality and for protection (e.g., searching for 'air filters'). The study also finds evidence suggestive of people sheltering at home and leaving their area on days with high exposure. In testing for heterogeneity by income, Burke et al. (2022) find lower search activity for protective items in lower income counties, and less likely to shelter at home, suggesting that individuals in wealthier counties have greater resource availability for potentially purchasing technologies to protect from the negative effects of the increased exposure, and have greater flexibility to stay at home. Furthermore, Yu et al (2024) find higher levels of PM2.5 in some counties in Northeast USA from the Canadian wildfire smoke in June 2023. Though this study doesn't focus on adaptation, the results find that these counties also have a higher percentage of persons of color or older adults, suggesting vulnerability differentials resulting from socio-demographic differences. In a more recent paper, Shen et al (2025) study mobility patterns in census blocks where evacuation was not imposed in response to the 2019 Kincade Fire in California. The results of the study show an increase in the time spent at home in the census blocks where median income is higher compared to lower income blocks before the fire, though the difference minimizes when measured for during the fire. Given the heterogeneity in exposure and mobility outcomes by socio-demographic variables we further add to the literature by focusing on mobility patterns of individuals affected by wildfire smoke in Spain by income thresholds.

In line with the findings from recent literature, the aspirations-capability framework (de Haas, 2021; Garip & Reed 2025; Hoffman 2024) provides a theoretical foundation for understanding why mobility may become more challenging in the wake of natural disasters. Carling (2002) explores the idea of involuntary immobility, suggesting how people who aspire to move, lack the resources and capabilities required for mobility. Though the theoretical analysis is broadly in the context of migration research, Carling (2002) highlights individual-level characteristics such as gender, age, and social class, to be important influences on available capabilities for mobility in general. In light of the current evidence on the social stratification patterns observed in short-term mobility after climate-related disasters, we think the aspirations-capability framework provides a relevant theoretical basis for understanding these trends. Accordingly, with this paper we add to the growing body of literature that asks who moves and who doesn't, by proximity to a large wildfire and exposure to wildfire-related PM2.5 in Spain between 2022-2025. In line with the aspirations-capability framework, we hypothesize that mobility patterns will be differentiated by vulnerability as defined by socioeconomic differences.

# Data

## *Mobile phone-derived dynamic population counts*

We utilised a mobility data product published by the Spanish Ministry of Transport, Mobility and Urban Agenda (hereafter MITMA) in a public online repository (MITMA, 2024). This dataset captures trips over 500 meters of over 13 million mobile phone users between Spanish districts from 2022 onwards. Original districts defined by Spanish National Statistical Office (INE) are aggregated into a coarser spatial unit where small and sparsely populated districts are grouped to incorporate areas not covered by antennas (Ponce-de Leon et al, 2021), resulting in a total of 3,792 districts. Our analysis focuses on the 3,566 districts located within mainland Spain, with a mean and median 2022 population of 12,522 and 6,143, respectively.

While the MITMA open mobility data provides various datasets on mobility based on district-level origin-destination hourly flows, in this study we specifically leverage the estimates on overnight stays. These data provide daily counts of the number of people staying overnight in each district<sup>1</sup>. Counts are further broken down by the home districts of those staying each night, based on previous patterns of mobility. These data were then used to compute the number of overnight stays in each district by residents of that district, as described in the Measures section of this paper.

## *Fire events*

The fire events used in our analysis were taken from data provided by the European Forest Fire Information System (EFFIS), compiled by the European Commission's Joint Research Centre (San-miguel-ayanz et al, 2012). EFFIS is the primary source of harmonised wildfire related information for Europe and analyses remotely sensed data to detect and map fire events, specifically using satellite imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS), and Sentinel-2. One of the core outputs of this analysis is burned area (BA) polygons, which incorporates the total area affected by each wildfire. Additional contextual information, such as start and end date of each fire, and the type of land cover burned during the event are also included.

We utilised the burned area dataset to identify fire events within mainland Spain during our study period based on their size. We focused only on large fires, using the threshold used by the Spanish government to classify a major wildfire, defined as those that burned at least 500 hectares (i.e., Grandes Incendios Forestales). Given their size, these fires have significant impacts on local environments, economies and population mobility, and often trigger evacuation orders. We found that although less than 5% of the fires in mainland Spain during 2022 were classified as major, they were responsible for more than 80% of the total burned area. Overall, we identify 104 unique large fires in the EFFIS data that occurred within mainland Spain between 2022 and 2024.

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<sup>1</sup> The data contains some missing days due to issues with data collection on these dates, although the number is small (less than 15 days over the entire 2022-2024 period).

### *Wildfire-Related Particulate Matter*

We included data on the daily surface concentration of wildfire-related particulate matter of less than 2.5 micrometers (PM 2.5) produced by Hänninen et al. (2022). This data relies on MODIS data that estimates the fire radiative power of wildfires from 2003-2024, and then an estimate of the dispersion of particulate matter resulting from these fires is produced via the SILAM chemical transport model. This estimate is expressed as a 0.1x0.1 degree grid over the European continent.

### *District-Level Income*

We make use of income data for the most recent year available, 2022, from the Household Income Distribution Atlas published by the Instituto Nacional de Estadística (INE). For this reason, district income is considered as time-invariant in our analysis. We incorporate median equivalized income for each district, which adjusts for regional differences in the size and structure of households. In rural areas where districts are agglomerated in the mobility dataset, we compute the mean of the median incomes of the districts included in each agglomeration. This measure captures community-level financial resources that may be mobilized in order to facilitate short-term residential displacement responses.

## **Estimation strategy**

### *Measures*

#### **Residential displacement**

To measure residential displacement, we use the MITMA overnight stays data. For each date ( $t$ ), we calculate the number of residential overnight stays in each district ( $i$ ), computed as the count of people staying overnight in each district that were designated as residents of that same district. This measure is then used as the outcome variable in all modelling.

In the context of this study, the use of overnight stays data has two advantages over the other MITMA mobility data that is available. Firstly, it ensures that the measure exclusively captures the mobility of residents of a given district and hence any other types of movement patterns (such as from first responders coming from outside of affected districts) are not able to influence model outputs. Secondly, by focusing on overnight stays rather than daytime movements, the measure captures larger changes in behaviour as opposed to routine or incidental mobility. Using the MITMA mobility data to compute a measure would make it impossible to exclusively capture the mobility of residents at the district level, and would shift the analysis more toward the association of wildfires on general mobility patterns rather than their effect on more substantial and policy-significant changes in population movements.

## Wildfire exposure

Wildfire exposure is captured from a daily measure at the district level as the population-weighted inverse distance to active fires, computed using gridded population data, fire polygons and district boundaries. This approach ensures both proximity to active wildfires and the size of expected impact in terms of exposed population are considered at the same spatial level as our residential displacement data. Gridded population data for 2021 at the 1km<sup>2</sup> resolution were obtained from Eurostat (2025) to allow the measure to account for the variation in population within districts. Fire polygons were taken from the EFFIS BA dataset with these used for all days a fire was considered active.

Firstly, on days during which there was an active fire, we calculated the distance of the final BA polygon to the centroid of each populated grid cell. To avoid division by zero during inverse-distance weighting, distances were constrained to a minimum of 500 m. This minimum distance was chosen to approximate within-cell distances given the spatial resolution of the gridded population data. Sensitivity analysis using alternative minimum distances of both 250 m and 1 km produced substantively similar model results (see Tables S2a-3c). Populated cells over 20 km away from an active fire were not considered, in line with the distance classifications used in prior research on population exposure to large wildfires (McBrien, et al., 2023; Wilner, et al., 2025).

For each grid cell, we then applied an inverse-distance weight to its population, producing a weighted exposure value. These cell-level values were then summed across all those within the district they lay within, yielding a single district-level exposure value weighted by population for each day when an active fire occurred.

The exposure of district  $i$  on day  $t$  is therefore expressed formally as:

$$Exposure_{i,f,t} = \sum_{c \in i} \frac{P_c}{D_c}$$

where  $P_c$  is the population of grid cell  $c$ ,  $D_c$  is the distance of the cell to active wildfire  $f$ . On days on which there were multiple active wildfires to the same districts, exposure values were summed to obtain a single, cumulative daily exposure measure for each district.

Finally, prior to modelling, we categorised the wildfire exposure measure into bins, in order to capture any non-linear associations with the measure and residential overnight stays. District-days with zero exposure were treated as a separate reference category (“No Exposure”). Among the observations with a positive exposure value, values were divided using the distribution of the non-zero exposure measure: Low Exposure corresponds to values between above 0 the median among non-zero values; Medium Exposure to between the median and the third quartile among non-zero values; and finally, High Exposure corresponds to values above the third quartile. This categorisation specification was chosen due to the measure being significantly right-skewed (see Table S1); splitting the measure into quartiles, for example, would produce two categories between zero and the median that would be very similar to each other in terms of values.

## Wildfire-related particulate matter exposure

To measure indirect wildfire hazard from poor air quality, we use the wildfire-related particulate matter data (see the above section) to calculate the population-weighted mean concentration of wildfire-related PM 2.5  $\mu\text{g}/\text{m}^3$  for each district-day in our analysis. This measure therefore captures spatiotemporal variations in wildfire-related exposure. Within our estimation, we treat wildfire-related PM 2.5 as a categorical variable according to the following levels: 0-1  $\mu\text{g}/\text{m}^3$  (reference level), 1-15  $\mu\text{g}/\text{m}^3$ , 15-30 $\mu\text{g}/\text{m}^3$  and >30  $\mu\text{g}/\text{m}^3$ . This permits us to observe potential nonlinear dynamics regarding wildfire-related PM 2.5 exposure and residential overnight stays. Furthermore, the threshold of 15 $\mu\text{g}/\text{m}^3$  corresponds to the 2021 World Health Organization (WHO) recommendations for short term exposure limits. Under these guidelines, exposure to PM 2.5 (non source specific) at this concentration for more than three or four days a year is sufficient to contain health risks, especially among vulnerable populations such as children and older adults (WHO, 2021).

### Modelling Approach

To estimate the association between human mobility with wildfire related hazards, we employ a Poisson regression model design with two-way fixed effects and an offset term to account for district population size. Specifically, we use the following specification:

$$\log(y_{it}) = \beta X + \alpha_i + \theta_{day(t)} + \delta_{month(t)} + \gamma_{year(t)} + \log(population_i)$$

Where:

- $y_{it}$  is the estimated number of residents spending the night in their home district  $i$  at date  $t$  (i.e. the measure to capture residential displacement),
- $\beta X$  is the presence of wildfire hazard (i.e., wildfire exposure measure and exposure to wildfire-related particulate matter),
- $\alpha_i$  is the fixed effects for district  $i$ ,
- $\theta_{day(t)}$  is the fixed effects for day of the week at date  $t$ ,
- $\delta_{month(t)}$  is the fixed effects for month at date  $t$ ,
- $\gamma_{year(t)}$  is the fixed effects for year at date  $t$ ,
- $\log(population_i)$  is the offset term, capturing the time-constant census population of each district, as provided by INE.

Our inclusion of an offset term ensures that our estimates can be interpreted relative to district population size, allowing us to model rates of overnight stays by residents rather than raw counts. Our fixed-effects design enables us to control for both unobserved differences between spatial units and time-specific shocks at the day of the week, month, and year levels. As a robustness check, we tested other specifications of time-fixed-effects and found consistent model results

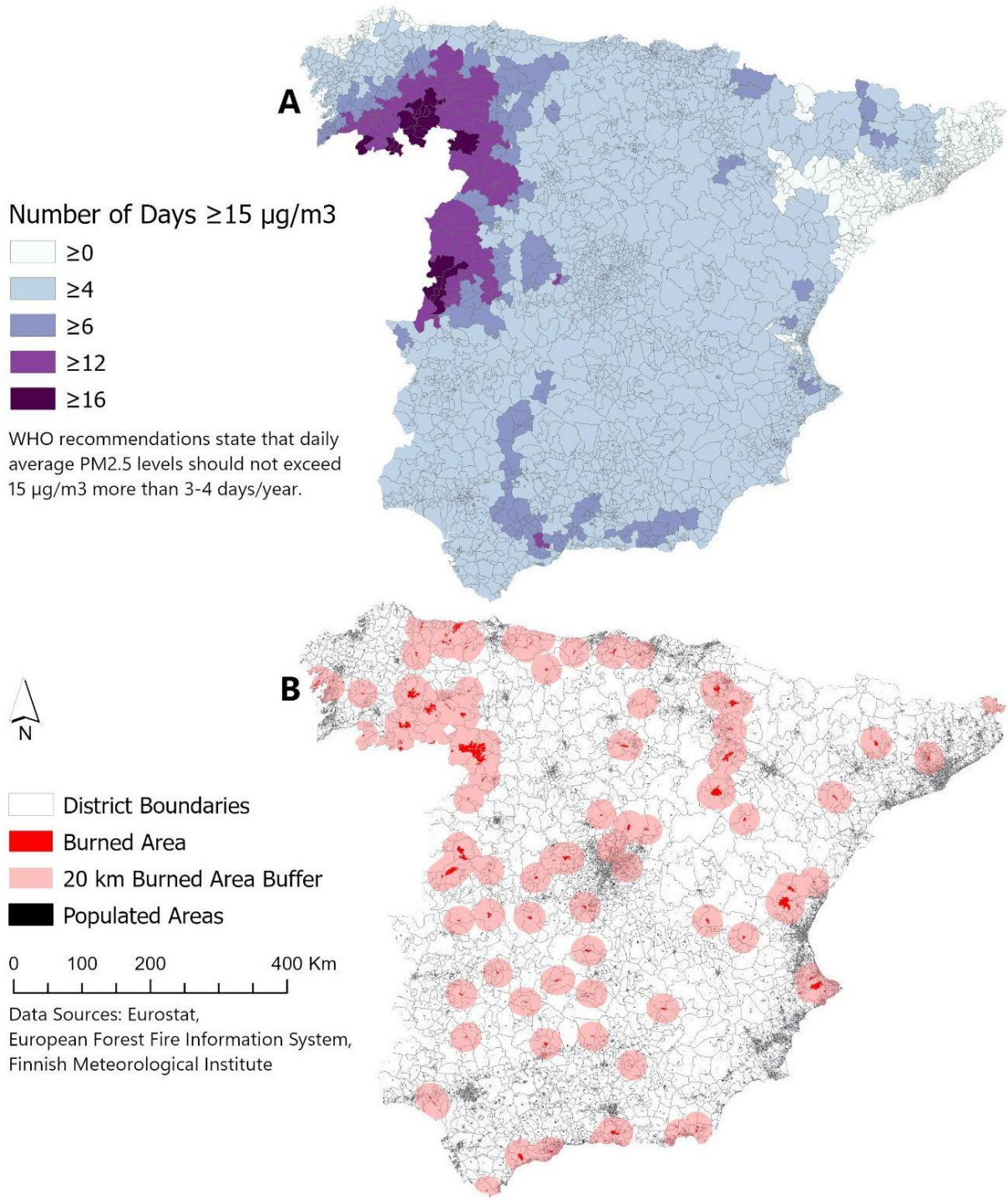
when date fixed effects were included within the model (see Table S2a). All model results are reported with robust standard errors clustered at the district level. This addresses any concerns around observations within the same district not being independent across time periods, a common issue within panel datasets.

## Results

### *Descriptive Results*

First, we display spatially the wildfire and air pollution data used in this study. Figure 1A illustrates the spatial distribution of major wildfires (larger than 500 hectares) in mainland Spain during the 2022-2024 study period, as well as a 5 km buffer zone surrounding each wildfire. Included on the map are also the districts available from the MITMA data that are used as the unit of analysis in our regression modelling, along with populated areas.

We observe that the major wildfires over our study period were more concentrated in certain areas of mainland Spain, with a high number of the fires in our dataset occurring in the north-western region. Moreover, unsurprisingly, rural parts of Spain are more heavily impacted by wildfire than major urban centres such as Madrid and Barcelona, and it is relevant to note that Spain is the country in Europe with the lowest density of settlements (Gutiérrez et al. 2023). The MITMA polygons further indicate that the districts experiencing or adjacent to fires are generally significantly larger than those in other parts of the country, reflecting the broader pattern of large wildfires occurring predominantly in sparsely populated areas. As discussed in the data section, districts used in the MITMA data are often larger or aggregated in rural areas to ensure adequate coverage.



*Figure 1. Number of Days Where Daily Mean Wildfire-related Particulate Matter Exceeded  $15 \mu\text{g}/\text{m}^3$  by district in Mainland Spain (A), and Burned Areas from Wildfires Larger than 500 Hectares in Mainland Spain (red), including a 20 km buffer surrounding each fire (pink) and populated areas at 1 km resolution (black) (B), both during 2022-2024.*

Figure 1B displays, for every district, the total number of days during the study period (2022-2024) where the daily mean wildfire particulate matter (PM) exceeded  $15 \mu\text{g}/\text{m}^3$ . We consider  $15 \mu\text{g}/\text{m}^3$  as a threshold in line with the 2021 World Health Organization (WHO) recommendations that daily average PM 2.5 should not exceed such a level for more than three or four days per year (WHO, 2021). However, WHO thresholds are formulated based on a systematic review of literature on adverse health outcomes associated with particulate matter from all sources. Recent literature on wildfire specific PM 2.5 has suggested that PM 2.5 from wildfires carries higher health risks than the same levels of PM 2.5 from non-wildfire sources (e.g. Aguilera et al., 2021). Therefore, this figure should be considered as a conservative estimate of the number of days wherein wildfire particulate matter poses health risks to the districts concerned, in the absence of any international guidelines concerning wildfire particulate matter specifically.

The regions most affected by high levels of wildfire particulate matter are expectedly the areas in north-western Spain where we observe many of the wildfires from Figure 1A. However, wildfire plumes often spread over larger areas beyond fire perimeters, and therefore a larger number of districts experience hazardous levels of wildfire-related particulate matter than those directly affected by the perimeter of the fire. We also observe that coastal areas, including Barcelona, are least affected by wildfire particulate matter exposure. While urban areas typically have higher levels of vehicle related PM 2.5, and other related pollutants such as Nitrogen Dioxide (NO<sub>2</sub>), we consider that rural or mountainous areas are conversely more exposed to wildfire related PM 2.5, given their proximity to large burnable areas.

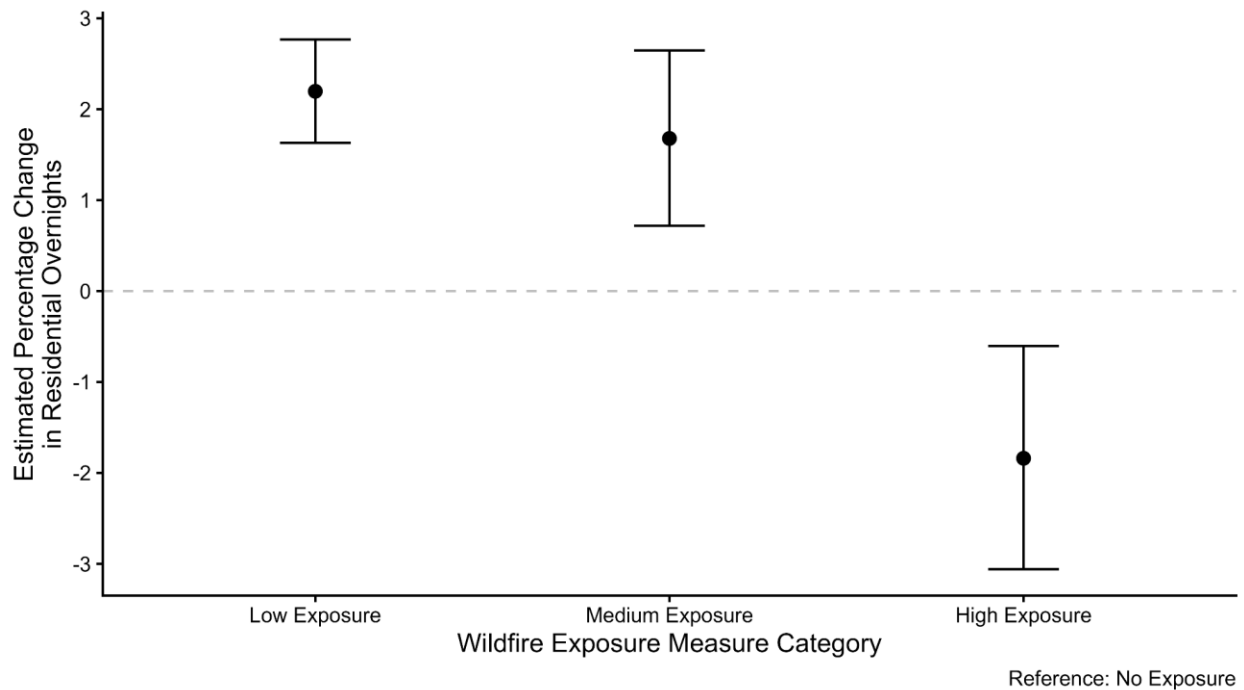
### *Modelling Results*

#### **The Impact of Wildfire Proximity**

Figure 2 displays the estimated percentage change of residential overnight stays associated with the binned wildfire exposure measure. Each value is shown in reference to the No Exposure category. Results suggest a non-linear relationship between the exposure measure and residential overnight stays. On district-days with low and medium exposure (i.e. below the third quartile of the measure), we find overnight stays increase among district residents. In contrast, on highly exposed district-days the opposite is true; in these cases we find the number of residents staying overnight in their home district is roughly 1.8% lower than on comparable days without nearby wildfire exposure.

These findings potentially reflect the policy interventions put in place in response to nearby wildfires by Spanish state authorities. Districts within the low and medium exposure category, though nearby to an active wildfire, may not be close enough to trigger an evacuation that would cause residential displacement. Indeed, our review of Spanish wildfire policies suggests that residents in areas close to wildfires are often advised to 'stay at home'. Many residents may also choose to stay at their home in order to protect property. In highly exposed areas, however, the decrease in residential overnight stays is likely to instead reflect evacuation orders or personal decisions of residents who feel they must flee their district to safety. This said, the estimated 1.8% reduction is relatively small in magnitude, though this is consistent with the possibility that some residents respond by relocating within their home district rather than leaving for another. This is a limitation with the level of MITMA data, which given the spatial level at which it is available,

obscures intra-district displacements. Also, here we report the same day impact on relocations and the cumulative relocations might be higher due to delayed mobility responses in following days.



*Figure 2. Percentage Change in Residential Overnight Stays Associated with Wildfire Exposure Measure with 95% Confidence Intervals*

Figure 3 displays the estimated marginal means, expressed as percentage change in number of residential overnight stays, associated with wildfire exposure measured by district income quartile. Under this model specification, we consider an interaction term of wildfire exposure and district income quartile. Full model results are available in Table S3a of the supplementary results.

As in Figure 2, among lower income districts (quartiles 1 and 2), at lower levels of wildfire exposure we observe an increase in the residential overnight stays. In district-days with higher exposure, however, districts in these quartiles exhibit little - if any - significant change in the number of residential overnights compared to the No Exposure category. Among the highest income districts (quartile 4), however, at both medium and high levels of wildfire exposure, we observe significant decreases in the number of residential overnight stays compared to all other income categories. In low exposure district-days, there is also a decrease in residential overnights among the wealthiest districts compared to both the first and second income quartiles.

Taken with Figure 2, then, these results suggest that the general decrease in residential overnight stays we observe across the whole dataset in the first model is driven largely by the behaviour of those in the wealthiest districts. Moreover, results presented in Figure 3 demonstrate a clear inequality in wildfire response across Spain's districts. Indeed, whilst in areas and periods of the highest exposure, the difference between districts by income is starkest, it persists across our wildfire exposure bins, with those in the wealthiest areas consistently more likely to move

themselves far enough away as to be out of their home district. This could be interpreted as due to the more substantial means individuals in these districts are able to draw upon - better access to transport, more resources to temporarily relocate, even additional properties outside of wildfire affected areas. Alternatively, the patterns we observe are consistent with contextual explanations; wealthier districts may have better access to services or infrastructure that makes evacuations from these areas easier to coordinate and implement for both residents and state authorities.

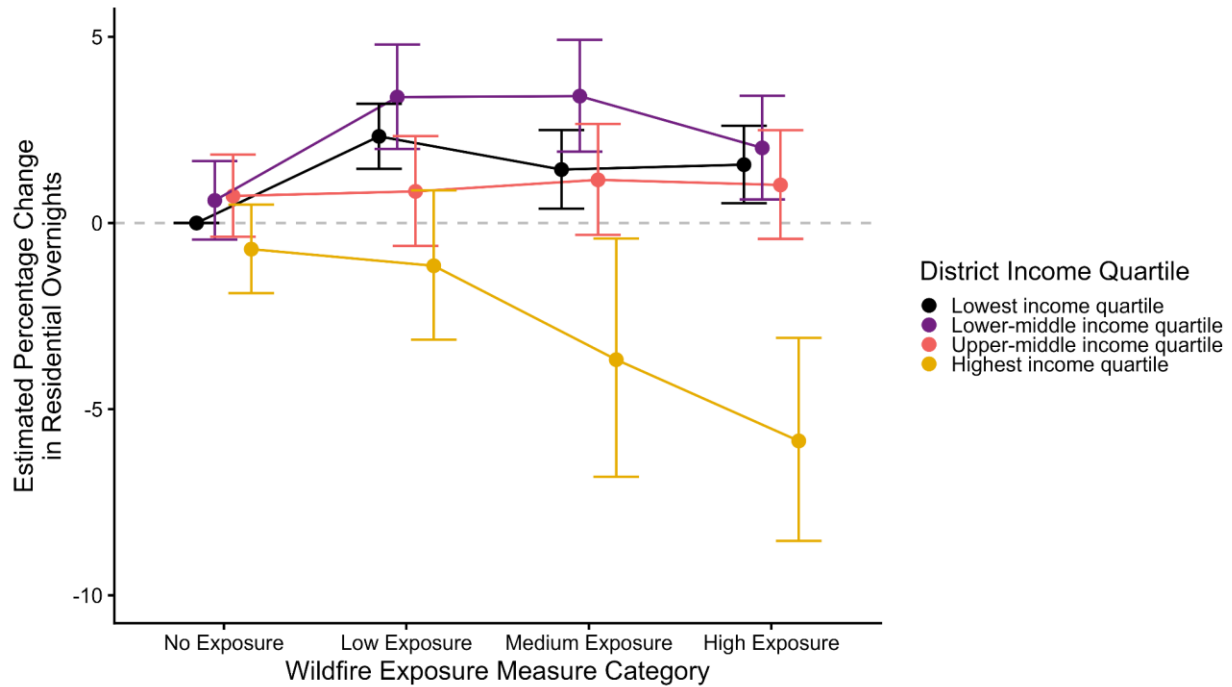
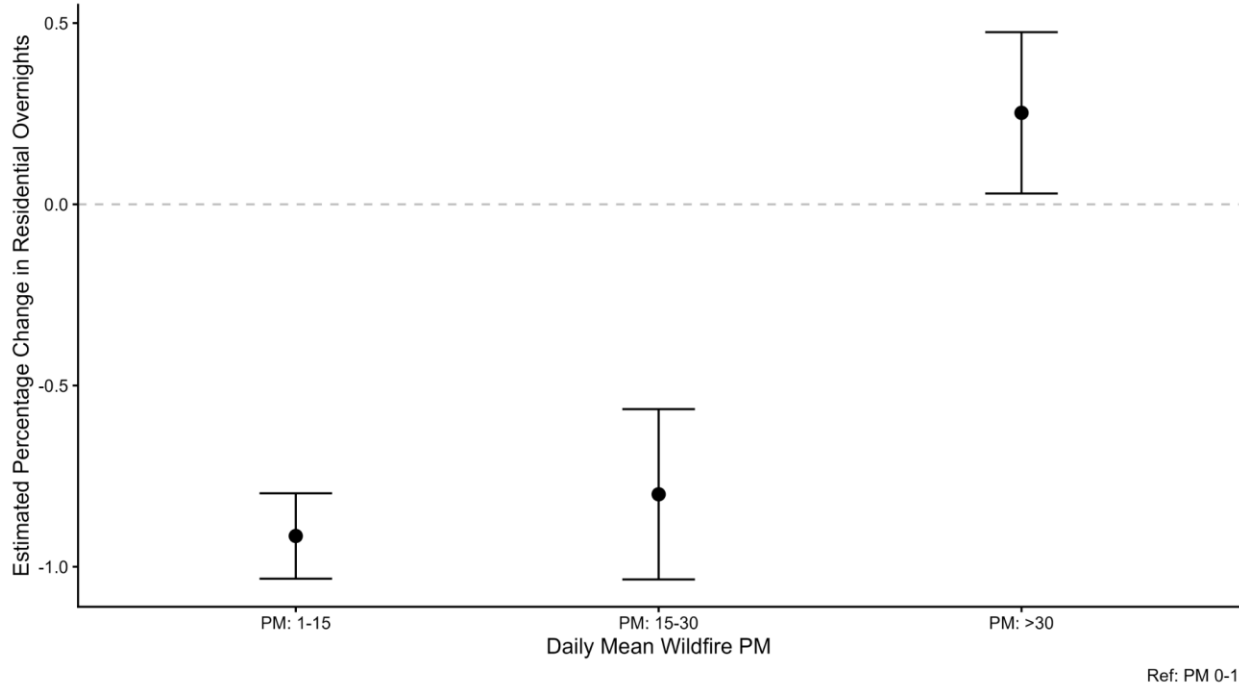


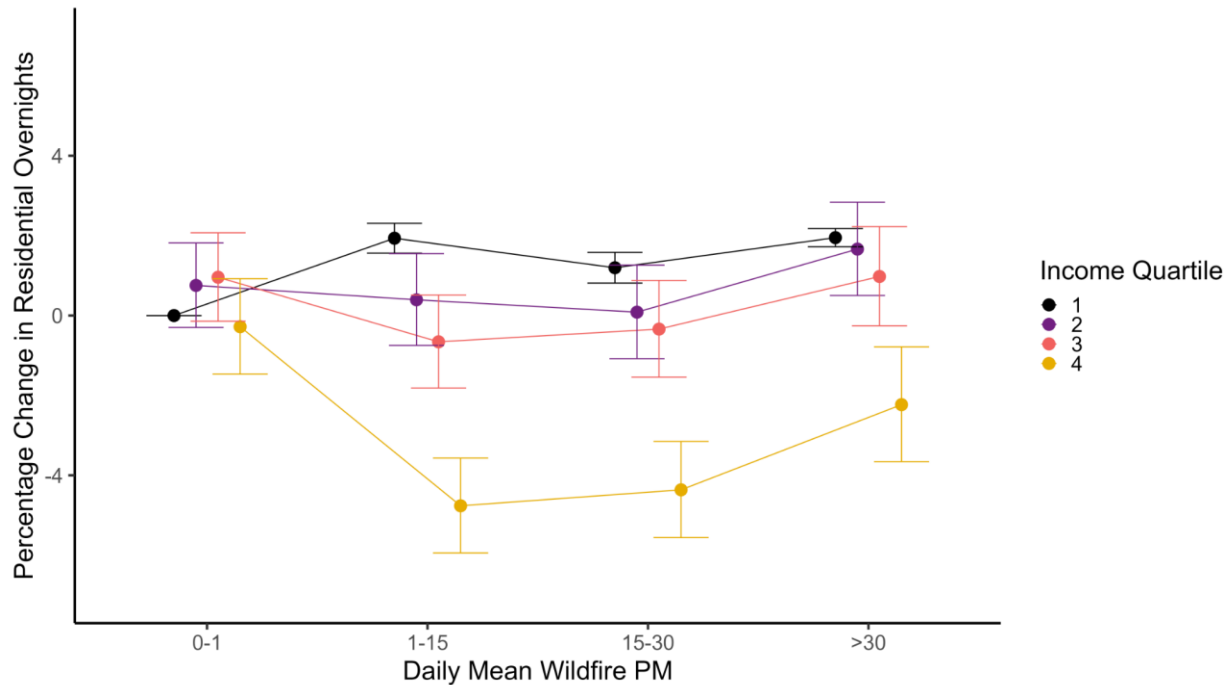
Figure 3. Percentage Change in Residential Overnight Stays Associated with Wildfire Exposure Measure: the Role of Median District Income with 95% Confidence Intervals

## The impact of Wildfire-Related Particulate Matter



*Figure 4. Percentage Change in Residential Stays Associated with Wildfire Particulate Matter with 95% Confidence Intervals*

Figure 4 displays the estimated percentage change of residential overnight stays associated with several levels of daily mean wildfire related particulate matter exposures. Circles denote point estimates and brackets denote 95 percent confidence intervals. Estimates for each level may be interpreted as compared to the reference value of wildfire particulate matter exposure: between 0 and 1  $\mu\text{g}/\text{m}^3$ . We observe no clear trend in changes in overnight stays when considering wildfire particulate matter exposure alone. Across levels, the magnitude of the point estimates is much smaller than what we observe in our results concerning wildfire proximity, and the direction of the effect is inconsistent. Model results are available in table S6 of the supplementary results: values are converted here to percentage change from the reference group for ease of interpretation.



*Figure 5. Percentage Change in Residential Stays Associated with Wildfire Particulate Matter: the Role of Median District Income with 95% Confidence Intervals*

Figure 5 displays the estimated percentage change in number of residential overnight stays associated with varying levels of daily mean wildfire related particulate matter exposures by district income quartile, compared to the reference group of 0-1  $\mu\text{g}/\text{m}^3$  and first distinct income quartile. Under this model specification, we consider an interaction term of wildfire particulate matter and district income quartile. Model results are available in table S7 of the supplementary results: values are converted here to percentage change from the reference group for ease of interpretation.

We observe a decrease in residential overnight stays only among the highest income district quartile, where daily mean particulate matter between 1-15  $\mu\text{g}/\text{m}^3$  and 15-30  $\mu\text{g}/\text{m}^3$  is associated with a decrease of 4.76 and 4.36 percent in residential overnight stays. Therefore, the inconclusive results seen in the previous figures might be considered as an average of heterogeneous behaviors according to district income. The stratification in residential displacement is greatest among the lower levels of particulate matter concentrations. This may be interpreted in light of mandatory evacuations that are likely contained within the district - days seeing over 30  $\mu\text{g}/\text{m}^3$  of wildfire related particulate matter.

Taken together, these results suggest that in the absence of strong state intervention via evacuation orders, residential displacement mirrors existing socioeconomic gradients. Residents in higher-income districts appear more able to anticipate wildfire risks and engage in voluntary relocation, while lower-income districts show more limited mobility options despite similar hazard exposure.

## Conclusion & Discussion

This study contributes new insights into the relationship between wildfire events and human mobility. First, we consider two forms of exposure to wildfires: proximity to wildfires as well as exposure to wildfire-related air pollution, where previous analyses typically consider one alone. Our analysis yields the following key findings. First, we descriptively observe that rural areas in Spain are more exposed to both wildfire proximity and wildfire-related PM 2.5 highlighting the importance of within-country spatial inequalities in discussing climate risks in the European context. Second, we find exposure to wildfires has a limited impact on the behaviour of residents in terms of mobility at the district level, except at higher levels of district-level exposure. Further, amongst high-income districts we observe significant residential displacement when exposure is less acute. Third, we find that exposure to wildfire-related PM 2.5 is associated with residential displacement uniquely among districts in the top quartile of median income. By leveraging high-frequency, spatially granular mobility data, we provide a comprehensive and robust analysis of behavioural change in response to wildfire hazards. In doing so, the study also demonstrates the potential of digital trace data to support social scientific inquiry, particularly in capturing human responses to environmental shocks at scale.

Our results highlight significant socioeconomic disparities between areas of Spain in their response to wildfire hazards. These patterns suggest that resource availability - whether personal, financial or infrastructural - plays a critical role in shaping adaptive capacity in general and capability to move in particular, as a response to wildfires. These findings add to the prior research from the United States on how socioeconomic inequalities mediate responses - and exposure - to climatic hazards (Deng et al., 2021; Lovekemp, 2018; Fussell et al., 2010). Overall, this study extends current understandings of how exposure, socioeconomic conditions moderate mobility-based adaptation to wildfire hazards, contributing insights from a non-North American context, a gap currently present in the literature.

While this study makes valuable contributions and offers insightful findings, several key limitations should be acknowledged when interpreting its results. Firstly, our mobility data is aggregated to the district level and, therefore, doesn't capture individual-level - or intradistrict - trends. As a result, we are unable to analyse variations in mobility patterns by demographic characteristics or any within-district heterogeneity. Similarly, wildfire data is temporally coarse and not able to show fires' impacts at the daily level; this said, the majority of the fires included in our analysis were active for two days or less, mitigating this problem somewhat. These limitations are, unfortunately, a consequence of the data on which this study relies. Another limitation of this aggregated data structure is that district level income is also correlated with urbanity and age, with lower-income districts also being more rural and older on average. While we consider income as a central driver of inequalities in mobility outcomes, our results may also be considered in light of these other overlapping inequalities. Additionally, this data also include first responders and other personnel attached to the suppression of the wildfires, creating uncertainties in the in- and outflow of the number of people. The strength of these data, however, is in their scale and statistical power. By leveraging them, we have been able to examine mobility patterns based on data from millions of Spanish residents, offering a robust and comprehensive view of aggregate trends. It should also be mentioned that the dates provided by EFFIS, on the wildfires lifespan, do not always overlap with other reports on the wildfires. In reality, individuals might therefore change their behaviour

due to each wildfire earlier than the registered start date, or continue with a change in behaviour past the registered end date. For the wildfire emission estimates, the used modelling framework could have considerable impacts on the implications on human mobility (v. Wees & v. d. Werf, 2019). The actual air pollution could also be above the WHO thresholds, independent of any current wildfires. Additionally, a small impact from a wildfire may also help cross these thresholds without being indicated in our analysis.

Our results, however, provide valuable insights into population-level responses, which can serve as a foundation for future research into the individual-level factors shaping mobility in the context of wildfire events. For instance, our findings can provide a basis for considering the temporal dimensions of these mobility patterns, with the goal of pinpointing anticipatory behavior, especially among the higher-income districts. More broadly, while our data carries statistical power, we do not have detailed individual level data as available in a typical social survey. Therefore, the consideration of risk perceptions, or other micro level determinants of mobility outcomes are outside the scope of this work. Future work could seek to complement these findings by the inclusion of further digital trace data to this, as in previous studies that utilise geolocalized Twitter data alongside natural language processing to understand mobility and sentiment in response to natural disasters (Wang and Taylor, 2018), or via a mixed-methods approach. Another way forward for this literature is to develop a comparative perspective. Typically, this literature (including this work at hand) focuses on one country's context/disaster at a time. For example, it would be instructive to compare these results to a similar analysis in Southern France or Northern Portugal. These regions host similar climates and wildfire risks to Spain, but socioeconomic differences in response may differ.

Further research is needed to investigate the specific mechanisms behind this adaptability gap, including the role of infrastructure, local governance, and investment in wildfire preparedness. Nevertheless, the implications are clear: residents in areas of Spain outside the wealthiest quartile face higher exposure to the social, economic, and health risks related to wildfires. The lack of proactive adaptation in these areas not only worsens outcomes during wildfire events but also contributes to the persistence of spatial and socioeconomic inequalities over time.

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## Supplementary materials

### *Sensitivity Analysis for Models on the Impact of Wildfire Proximity*

This section relates to the analysis presented in the main paper for models that include the wildfire exposure measure (as shown in Figures 2 and 3 of the main paper). The tables below present the results of sensitivity analyses conducted to stress-test these results. Sensitivity analysis was conducted by varying the specification of the time-fixed effects used in the models and the minimum distance used to compute the wildfire exposure metric.

As outlined in the paper's methods section, the wildfire exposure measure that was computed for use in the analysis utilised a minimum distance from a population grid to a fire burned area polygon of 500m. This was used to prevent a division by zero during the calculation of the measure; 500m was chosen specifically because of the population grid cell resolution (1km<sup>2</sup>).

Table S1 presents a summary of the positive values of the computed wildfire exposure measure for different minimum values: 500m (as in the main specification), 250m, and 1,000m. The latter two were used in the sensitivity analyses of regression models outlined in the rest of this section. The values shown in Table S1 are used, as outlined in the paper's methods section, as thresholds to categorise the measure into exposure bins, used as the main independent variables in modelling. The summary table shows only minor differences among the three minimum distances. At higher values, however, differences are clearer: when 1,000m is used as the minimum distance, the measure's distribution is more compressed in the upper range, with a lesser right skew; when 250m is used, the opposite is the case.

*Table S1: Summary Table of Positive Wildfire Exposure Measure Values Computed Using Different Minimum Distances (500m, 250m and 1,000m)*

	500m	250m	1,000m
Minimum	0.000051	0.000051	0.000051
1st Quartile	0.087554	0.087554	0.087554
Median	0.339063	0.339063	0.339063
Mean	0.966403	1.054165	0.893761
3rd Quartile	0.949256	0.967523	0.915000
Maximum	25.59361	26.82194	24.70721
N	5,409	5,409	5,409

Table S2a shows the regression output for the results presented in Figure 2 of the manuscript, in which day of the week, month and year fixed-effects were used (Model 1a). Next to this is the output for the same model, with date fixed effects (Model 1b). Both models use the standard wildfire exposure measure, with a minimum distance of 500 m used to calculate it.

Model 1b produces coefficients that are similar in direction and relative magnitude to those in the baseline model (Model 1a). However, the magnitude of the coefficient for the High Exposure category of the wildfire exposure measure decreases. Further, it is no longer statistically significant at the 95% level, though it remains significant at the 90% level ( $p = 0.079$ ). The change in statistical significance is not unexpected, as the inclusion of date fixed effects further absorbs temporal shocks and reduces the identifying variation used to estimate the effect.

*Table S2a: Model Results: Residential Stays Associated with Wildfire Exposure Measure. Varying Time Fixed-Effect Specifications; Minimum Distance Set at 500m*

	Model 1a	Model 1b
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Reference: No Exposure		
Low Exposure	0.0217*** (0.0029)	0.0332*** (0.0030)
Medium Exposure	0.0167*** (0.0048)	0.0262*** (0.0052)
High Exposure	-0.0186** (0.0064)	-0.0113. (0.0064)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784

BIC	123,647,723.7	107,074,383.6
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Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

Table S2b displays the same output as Table S2a, but with the minimum distance for the wildfire exposure measure set at 250m. Model 1c is the output with day of the week, month and year time fixed effects; Model 1d is the output which employs date fixed effects. Results very closely match those in Table S2a.

*Table S2b: Model Results: Residential Stays Associated with Wildfire Exposure Measure. Varying Time Fixed-Effect Specifications; Minimum Distance Set at 250m*

	Model 1c	Model 1d
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Reference: No Exposure		
Low Exposure	0.0217*** (0.0028)	0.0331*** (0.0030)
Medium Exposure	0.0168*** (0.0048)	0.0262*** (0.0052)
High Exposure	-0.0186** (0.0064)	-0.0113. (0.0064)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,647,647.6	107,074,360.5

Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

Table S2c displays the same output as Table S2a, but with the minimum distance for the wildfire exposure measure set at 1000m. Model 1e is the output where time fixed effects are day of the week, month and year; Model 1f employs date fixed effects instead. Results very closely match those in Table S2a. Model 1f, the most conservative of the models run, shows that the coefficient for the High Exposure category of the wildfire exposure measure is no longer significant at the 90% level ( $p = 0.101$ ). Given its specification, this is not unexpected: the date fixed effects absorb a large portion of the variance in residential overnight stays, and setting the minimum distance to 1000m reduces the impact of districts with populations very close to wildfire burned area polygons on the overall exposure measure.

*Table S2c: Model Results: Residential Stays Associated with Wildfire Exposure Measure. Sensitivity Analysis - Varying Time Fixed-Effect Specifications; Minimum Distance Set at 1000m*

	Model 1e	Model 1f
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Reference: No Exposure		
Low Exposure	0.0217*** (0.0028)	0.0332*** (0.0030)
Medium Exposure	0.0158*** (0.0048)	0.0248*** (0.0052)
High Exposure	-0.0180** (0.0064)	-0.0105 (0.0064)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,648,324.3	107,075,294.5

Signif. codes: '\*\*\*' =  $p < 0.001$ ; '\*\*' =  $p < 0.01$ ; '\*' =  $p < 0.05$ ; '.' =  $p < 0.1$

The next three tables (Table S3a, Table S3b, and Table S3c) have the same format as the previous three, but show the model outputs for the interaction between wildfire exposure and district income quartile, as displayed in Figure 3 in the main paper. As above, model outputs across time fixed effect specifications and variations in the computation of the exposure measure remain in line with the model results shown in the main paper. Importantly, the main conclusion from this model in the paper - namely that across exposure levels, the districts with the highest incomes see the largest reductions in residential overnight stays - remains consistent.

*Table S3a: Model Results: Residential Stays Associated with Wildfire Exposure Measure and Income Interactions - Varying Time Fixed-Effect Specifications; Minimum Distance Set at 500m*

	Model 2a	Model 2b
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Reference: No Exposure		
Low Exposure	0.0290*** (-0.0044)	0.0380*** (-0.0051)
Medium Exposure	0.0215*** (-0.0053)	0.0288*** (-0.0066)
High Exposure	0.0085 (-0.0052)	0.0197** (-0.0062)
Reference: Median Income Quartile 1 (Lowest Income)		
Median Income Quartile 2	0.006 (-0.0053)	0.0049 (-0.0054)
Median Income Quartile 3	0.0072 (-0.0056)	0.0062 (-0.0056)
Median Income Quartile 4	-0.007 (-0.0061)	-0.0008 (-0.0061)
Low Exposure x Median Income Quartile 2	0.0042 (-0.0059)	0.0096 (-0.0065)
Medium Exposure x Median Income Quartile 2	0.0132. (-0.0072)	0.0196* (-0.0087)
High Exposure x Median Income Quartile 2	-0.0016 (-0.0068)	-0.0055 (-0.0078)

Low Exposure x Median Income Quartile 3	-0.0218*** (-0.0064)	-0.0198** (-0.0069)
Medium Exposure x Median Income Quartile 3	-0.01 (-0.0072)	-0.0097 (-0.0084)
High Exposure x Median Income Quartile 3	-0.0126. (-0.0071)	-0.0180* (-0.008)
Low Exposure x Median Income Quartile 4	-0.0275** (-0.0093)	-0.0298*** (-0.0089)
Medium Exposure x Median Income Quartile 4	-0.0446** (-0.0159)	-0.0484** (-0.016)
High Exposure x Median Income Quartile 4	-0.0688*** (-0.0151)	-0.0746*** (-0.0156)

Fixed-Effects:

District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes

S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,580,737.8	107,035,426.1

Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

*Table S3b: Model Results: Residential Stays Associated with Wildfire Exposure Measure and Income Interactions - Varying Time Fixed-Effect Specifications; Minimum Distance Set at 250m*

	Model 2c	Model 2d
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays

Reference: No Exposure

Low Exposure 0.0290\*\*\* (0.0044) 0.0380\*\*\* (0.0051)

Medium Exposure 0.0221\*\*\* (0.0053) 0.0295\*\*\* (0.0066)

High Exposure 0.0081 (0.0053) 0.0193\*\* (0.0063)

Reference: Median Income Quartile 1  
(Lowest Income)

Median Income Quartile 2 0.0060 (0.0053) 0.0049 (0.0054)

Median Income Quartile 3 0.0072 (0.0056) 0.0062 (0.0056)

Median Income Quartile 4 -0.0070 (0.0061) -0.0008 (0.0061)

Low Exposure x Median Income Quartile 2 0.0042 (0.0059) 0.0096 (0.0065)

Medium Exposure x Median Income Quartile 2 0.0125. (0.0072) 0.0186\* (0.0087)

High Exposure x Median Income Quartile 2 -0.0012 (0.0069) -0.0049 (0.0079)

Low Exposure x Median Income Quartile 3 -0.0218\*\*\* (0.0064) -0.0198\*\* (0.0069)

Medium Exposure x Median Income Quartile 3 -0.0107 (0.0072) -0.0106 (0.0084)

High Exposure x Median Income Quartile 3 -0.0121. (0.0071) -0.00014

Low Exposure x Median Income Quartile 4 -0.0279\*\* (0.0093) -0.0303\*\*\* (0.0089)

Medium Exposure x Median Income Quartile 4 -0.0446\*\* (0.0158) -0.0485\*\* (0.0159)

High Exposure x Median Income Quartile 4 -0.0685\*\*\* (0.0152) -0.0742\*\*\* (0.0156)

Fixed-Effects:

District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,580,729.30	107,035,499.60

Signif. codes: '\*\*\*' =  $p < 0.001$ ; '\*\*' =  $p < 0.01$ ; '\*' =  $p < 0.05$ ; '.' =  $p < 0.1$

*Table S3c: Model Results: Residential Stays Associated with Wildfire Exposure Measure and Income Interactions - Varying Time Fixed-Effect Specifications; Minimum Distance Set at 1000m*

	Model 2e	Model 2f
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Reference: No Exposure		
Low Exposure	0.0290*** (0.0044)	0.0380*** (0.0051)
Medium Exposure	0.0224*** (0.0052)	0.0297*** (0.0064)
High Exposure	0.0078 (0.0053)	0.0191** (0.0063)
Reference: Median Income Quartile 1 (Lowest Income)		
Median Income Quartile 2	0.0060 (0.0053)	0.0049 (0.0054)
Median Income Quartile 3	0.0072 (0.0056)	0.0062 (0.0056)

Median Income Quartile 4	-0.0070 (0.0061)	-0.0008 (0.0061)
Low Exposure x Median Income Quartile 2	0.0042 (0.0059)	0.0096 (0.0065)
Medium Exposure x Median Income Quartile 2	0.0103 (0.0073)	0.0158. (0.0086)
High Exposure x Median Income Quartile 2	0.0010 (0.0069)	-0.0024 (0.0080)
Low Exposure x Median Income Quartile 3	-0.0218*** (0.0064)	-0.0198** (0.0069)
Medium Exposure x Median Income Quartile 3	-0.0102 (0.0071)	-0.0098 (0.0083)
High Exposure x Median Income Quartile 3	-0.0124. (0.0072)	-0.00014
Low Exposure x Median Income Quartile 4	-0.0275** (0.0093)	-0.0298*** (0.0089)
Medium Exposure x Median Income Quartile 4	-0.0455** (0.0159)	-0.0492** (0.0159)
High Exposure x Median Income Quartile 4	-0.0681*** (0.0152)	-0.0740*** (0.0156)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
<hr/>		
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,581,110.30	107,036,132.20

Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

Next, we rerun the main analysis (with minimum distance as 500m) but with the wildfire exposure measure log-transformed plus 1 (to account for the large number of zeroes), instead of binned. The results of this analysis are shown in Table S4 and S5 for outcome measure only and with income interactions, respectively, both with varying fixed effects specifications. Results show a similar pattern as in the binned exposure measure in the main models, as in Table S2a and S3a.

*Table S4: Model Results: Residential Stays Associated with Wildfire Exposure Measure Log(x+1) Transformed. Varying Time Fixed-Effect Specifications*

	Model 1g	Model 1h
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Log(Exposure+1)	-0.0136** (0.0049)	-0.0088. (0.0050)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,652,711.6	107,091,752.2

Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

*Table S5: Model Results: Residential Stays Associated with Wildfire Exposure Measure Log(x+1) Transformed and Income Interactions. Varying Time Fixed-Effect Specifications*

	Model 2e	Model 2f
Dependent Var.:	Residential Overnight Stays	Residential Overnight Stays
Log(Exposure+1)	0.0075* (0.0030)	0.0143*** (0.0036)
Reference: Median Income Quartile 1 (Lowest Income)		
Median Income Quartile 2	0.0060 (0.0053)	0.0049 (0.0054)
Median Income Quartile 3	0.0072 (0.0056)	0.0062 (0.0056)
Median Income Quartile 4	-0.0071 (0.0061)	-0.0008 (0.0061)
Log(Exposure+1) x Median Income Quartile 2	0.0022 (0.0044)	0.0014 (0.0051)
Log(Exposure+1) x Median Income Quartile 3	-0.0103* (0.0041)	-0.0129** (0.0047)
Log(Exposure+1) x Median Income Quartile 4	-0.0504*** (0.0077)	-0.0543*** (0.0083)
Fixed-Effects:		
District	Yes	Yes
Day of the Week	Yes	No
Month	Yes	No
Year	Yes	No
Date	No	Yes
S.E.: Clustered	District	District
Observations	3,803,066	3,803,066
Squared Cor.	0.99698	0.99793
Pseudo R2	0.99750	0.99784
BIC	123,580,074.4	107,047,139.2

Signif. codes: '\*\*\*' = p<0.001; '\*\*' = p<0.01; '\*' = p<0.05; '.' = p<0.1

Figure S1: Daily Lags and Leads for Model 1 with Main Specification with Binary Fire Exposure (High = 1 All Else = 0)

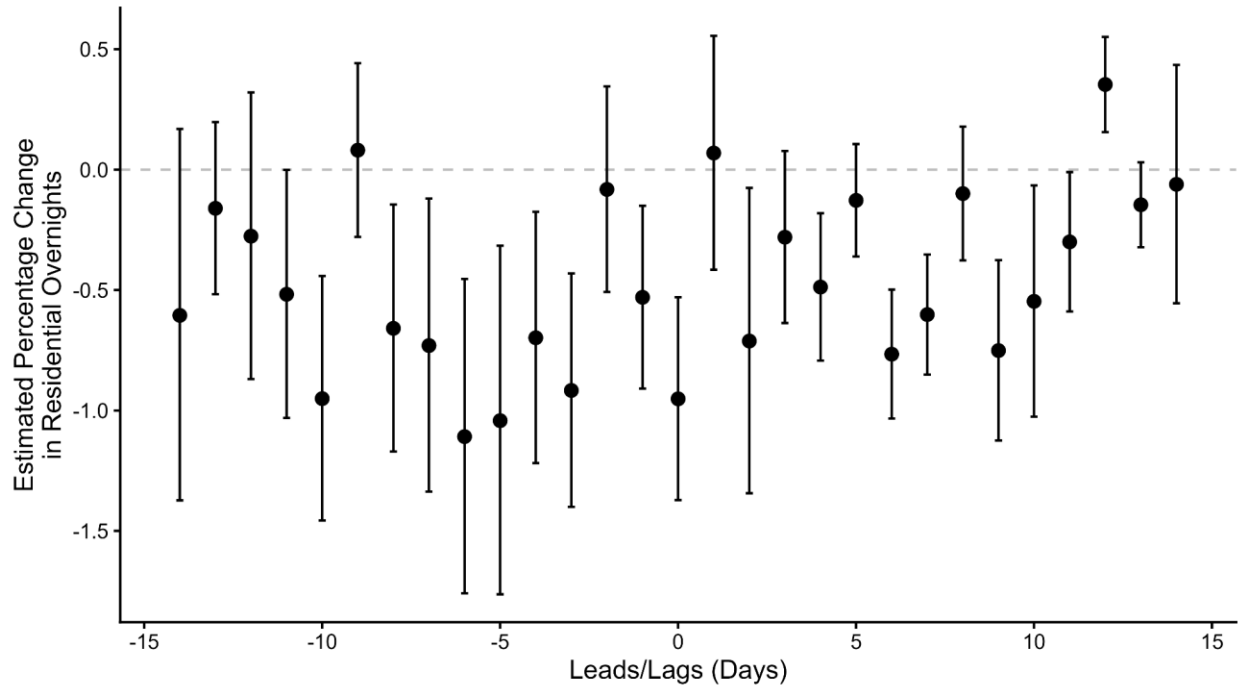
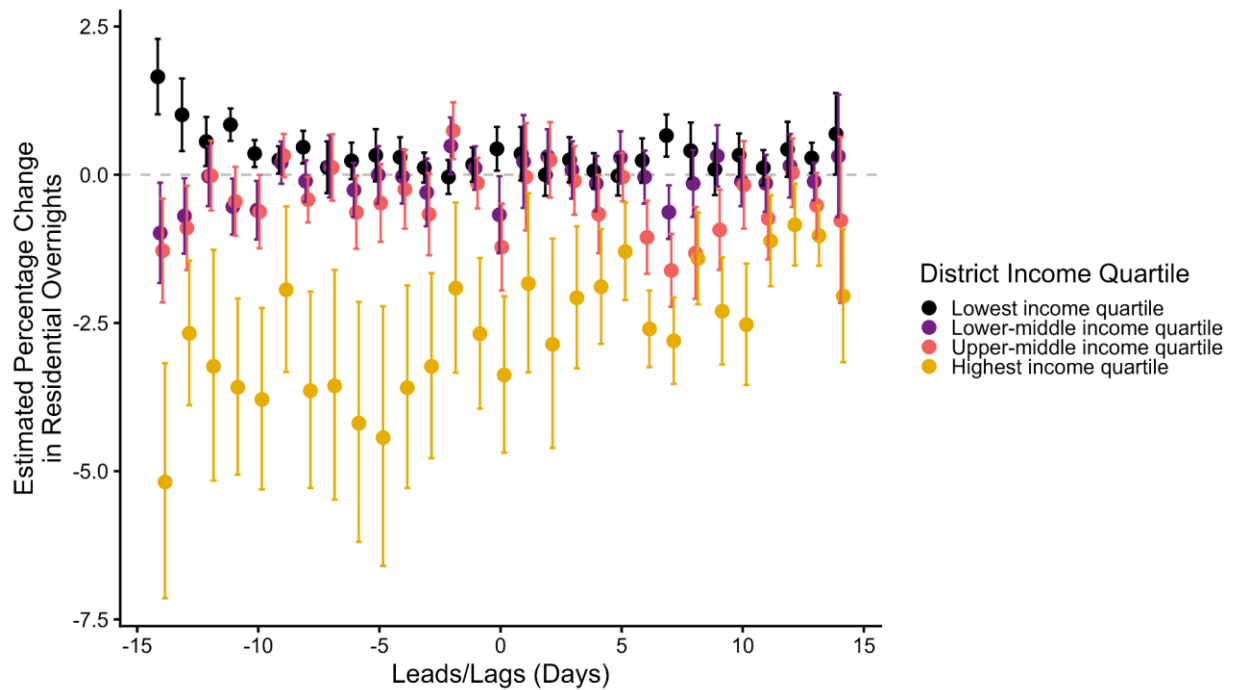


Figure S2: Daily Lags and Leads for Model 2 with Main Specification with Binary Fire Exposure (High = 1 All Else = 0)



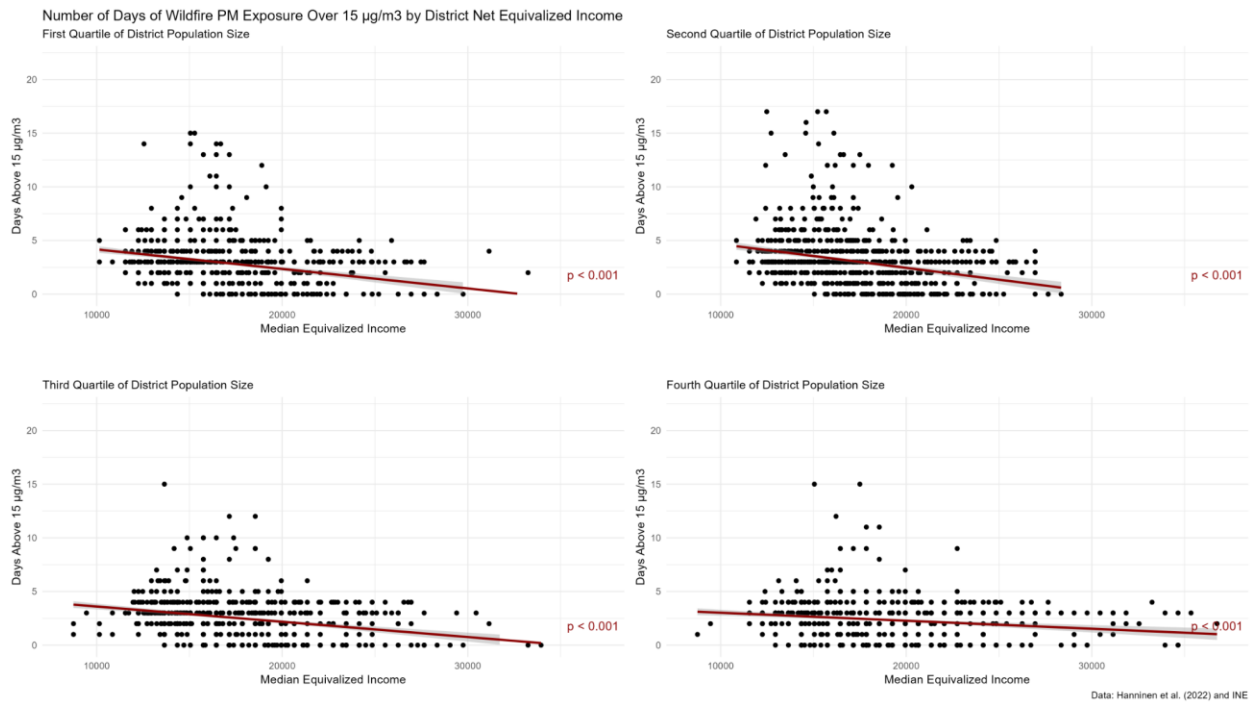


Table S6: Model Results: Residential Stays Associated with Wildfire Particulate Matter

	m1	m1b
Dependent Var.:	persons_staying_overnight	persons_staying_overnight
pm_bins1-15	-0.0032*** (0.0007)	-0.0092*** (0.0006)
pm_bins15-30	-0.0047** (0.0015)	-0.0080*** (0.0012)
pm_bins>30	-0.0027* (0.0013)	0.0025* (0.0011)
Fixed-Effects:		
date	Yes	No
overnight_stay_district	Yes	Yes

weekday_factor	No	Yes
year_factor	No	Yes
month_factor	No	Yes
S.E.: Clustered	overnight_stay_district	overnight_stay_district
Observations	3,803,066	3,803,066
Squared Cor.	0.99793	0.99699
Pseudo R2	0.99784	0.99750
BIC	107,082,491.3	123,499,922.1

*Table S7: Model Results in Residential Stays Associated with Wildfire Particulate Matter and Income Interactions*

	m2	m2b
Dependent Var.:	persons_staying_overnight	persons_staying_overnight
pm_bins1-15	0.0327*** (0.0019)	0.0267*** (0.0019)
pm_bins15-30	0.0249*** (0.0023)	0.0214*** (0.0019)
pm_bins>30	0.0012 (0.0016)	0.0165*** (0.0011)
median_income_quartile2	0.0065 (0.0054)	0.0075 (0.0054)
median_income_quartile3	0.0087 (0.0056)	0.0095. (0.0056)
median_income_quartile4	0.0035 (0.0061)	-0.0028 (0.0061)
pm_bins1-15 x median_income_quartile2	-0.0223*** (0.0029)	-0.0227*** (0.0029)
pm_bins15-30 x median_income_quartile2	-0.0190*** (0.0036)	-0.0186*** (0.0032)
pm_bins>30 x median_income_quartile2	-0.0023 (0.0023)	-0.0103*** (0.0025)
pm_bins1-15 x median_income_quartile3	-0.0379*** (0.0027)	-0.0353*** (0.0027)

pm_bins15-30 x median_income_quartile3	-0.0285*** (0.0035)	-0.0248*** (0.0033)
pm_bins>30 x median_income_quartile3	-0.0097*** (0.0024)	-0.0191*** (0.0029)
pm_bins1-15 x median_income_quartile4	-0.0666*** (0.0035)	-0.0652*** (0.0034)
pm_bins15-30 x median_income_quartile4	-0.0577*** (0.0037)	-0.0537*** (0.0033)
pm_bins>30 x median_income_quartile4	-0.0234*** (0.0035)	-0.0391*** (0.0040)

Fixed-Effects:

date	Yes	No
overnight_stay_district	Yes	Yes
weekday_factor	No	Yes
year_factor	No	Yes
month_factor	No	Yes

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S.E.: Clustered	overnight_stay_district	overnight_stay_district
Observations	3,803,066	3,803,066
Squared Cor.	0.99800	0.99705
Pseudo R2	0.99786	0.99753
BIC	105,832,772.1	122,245,461.5

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