Adaptive Migration in the Face of Wildfires: Financial Constraints and the Role of Government Aid

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Abstract

Natural disasters are expected to impact a large and increasing number of people with climate change. The movement from risky to safe areas – "adaptive migration" – is theorized to be a key strategy for minimizing the costs of natural disasters. This paper provides novel empirical estimates of the extent of adaptive migration, highlights financial constraints as a barrier, and identifies the causal impact of government disaster aid receipt on migration in the context of California, where fires have become more frequent and severe. Using detailed individual-level geographic data, I estimate the effect of wildfires on migration using a difference-in-differences (DID) event study design by comparing the migration behavior before and after a fire of individuals in census blocks that are burned for the first time with that of those in never-burned blocks within a census tract. I find that an individual experiencing a first fire has a 6.5-percentage-point (p.p.) higher probability of out-migration after four years, an 18.5% increase. Those who experience a fire are not more likely to be in safe areas. However, individuals less likely to be financially constrained after the fire (i.e. those with high credit scores) are more likely to move to safe areas after four years. Leveraging a new instrument for aid receipt – taking advantage of the fact that politically competitive counties are more likely to receive aid – I find that government aid is associated with higher migration, albeit not to safe areas. Overall, migration is occurring, but adaptive responses are small. Moreover, government aid could be redesigned to improve the level of adaptive migration out of risky areas.

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1 Introduction

Climate change is increasing the number and severity of natural disasters such as floods, hurricanes, and wildfires (Berlemann and Steinhardt, 2017; Benevolenza and DeRigne, 2019; Yao et al., 2023). These natural disasters impose an enormous human and economic toll, affecting 93.1 million worldwide and costing $202.7 billion in 2023 alone (OCHA, 2024). The costs of climate change, however, can be mitigated through adaptation. Governments and individuals can take a variety of actions to reduce the harms of these disasters and limit these costs, including promoting innovation (Desmet et al., 2018; Cruz and Rossi-Hansberg, 2023), modifying trade (Kleinman et al., 2023; Desmet and Rossi-Hansberg, 2024), increasing building resiliency (Baylis and Boomhower, 2021), and investing in preventative infrastructure (Fried, 2022; Hsiao, 2023).

Migration is theorized to be another important adaptation mechanism. In order for migration to be climate adaptive, it is not enough for individuals to move away from a location that is affected by a disaster: They must move to an area that has lower risk. I define migration to a low-risk area as "adaptive migration." Since climate change will impact areas differently (Flannigan et al., 2000; Keeley and Syphard, 2016), with some becoming more dangerous and others safer, population movements to safer areas can lower the cost of natural disasters. Indeed, using dynamic spatial equilibrium models, researchers have found that shutting down migration generates the largest welfare losses from climate change, even after accounting for other adaptive measures (Desmet and Rossi-Hansberg, 2015; Conte et al., 2022; Cruz and Rossi-Hansberg, 2023; see Desmet and Rossi-Hansberg, 2024 for a review).[1] However, there is limited empirical evidence documenting the extent to which populations actually respond to natural disasters by moving adaptively – that is, to less risky areas. The key difficulty in assessing long-run migration patterns is the absence of individual-level panel data with granular location information.

This paper provides novel empirical results that quantify the extent to which people adaptively migrate after a climate shock, explores who does so, and investigates the role of financial tools and government aid in facilitating or hindering this process by studying migration responses to California wildfires. California is the ideal setting for my study of these questions for two reasons. First, half of the most destructive fires California has experienced since it began keeping records in the early 1900s have occurred in the past two decades (WFCA, 2024), with substantial public resources dedicated to assisting those impacted by wildfires. In 2020, federal assistance for California wildfires alone topped $103 million (FEMA, 2021). An increasing number of people are expected to be impacted by this climate shock in California and the world, highlighting a need to understand how individuals and governments can best respond to these events. Second, wildfires often force

[1] Bilal and Rossi-Hansberg (2023) find that shutting down migration in their model has a small effect on the average welfare loss of individuals. This is they model individuals as considering economic opportunities in their migration decisions. For the US context, they find that the correlation between areas that are desirable in climate terms and those desirable in economic development terms is close to zero, and so the benefits of moving, considering these dimensions within welfare, are minimal. They acknowledge that, in other contexts, there are large welfare losses from shutting down migration. My paper provides further evidence that adaptive migration is empirically minimal.

people to evacuate, at least temporarily, and occur in high-risk areas, making the climate risk of the area particularly salient to residents (McCaffrey et al., 2018; McCoy and Walsh, 2018; Anderson et al., 2023). If adaptive migration does happen, this should be a setting in which to find it. The fact that I find minimal evidence of adaptive migration suggests that it is unlikely to occur in other contexts.

Using detailed location data from the University of California Consumer Credit Panel (UCCCP) and Infutor Data Solutions, I can follow individuals' locations over time to distinguish between temporary displacement (i.e. moves within the first two years after the wildfire) and adaptive migration, which is characterized by long-term moves away from high-risk areas, overcoming one of the main challenges in studying adaptive migration. I can also investigate the role of financial institutions and government aid in influencing people's migration decisions and assess the extent to which these factors help facilitate adaptive migration.

To quantify the extent of migration, I conduct a stacked difference-in-differences (DID) event study to incorporate information from multiple wildfires as natural experiments. I compare the migration decisions before and after a fire of individuals living in census blocks burned by a fire for the first time, with those of individuals living in census blocks never burned within the same census tract and year.[2] By comparing individuals in census blocks burned for the first time and those never burned, I can cleanly identify the impact of the fire on migration responses and avoid the "forbidden comparisons" flagged in the recent DID literature (Callaway and Sant'Anna, 2021; Baker et al., 2022; de Chaisemartin and D'Haultfoeuille, 2022; Roth et al., 2023).[3] I also consider the impact of megafires, which burn over 100,000 acres and the impact of subsequent fires (i.e. second vs. first, third vs. second fire). Finally, I investigate how receiving government aid affects these migration decisions. I focus on two main outcomes: whether individuals move away and whether they move to a low- or medium- risk location, which I also call safe areas.[4]

Overall, there is minimal evidence of adaptive migration. People living in census blocks hit by a fire for the first time are 10.6 percentage points (p.p.) more likely to be in a different census tract the year after the fire, which corresponds to a 79.4% increase in the probability of moving. The results are not solely due to forced migration: Though individuals whose houses are damaged experience a 123.3% increase in their likelihood of being in a different tract the year after the fire, those whose houses are not damaged also experience a 22.8% increase. In the longer run, after four

[2] Census blocks are the smallest geography defined by the US Census Bureua, which creates census geographies to create statistical areas bounded by visible features (Rossiter, 2011). A census block falls within a census tract, which is determined to have an ideal population of 4,000 people (Bureau, 2022). Half of the census blocks within the United States are smaller than a tenth of a square mile (Lynch, 2020).

[3] Forbidden comparisons are an issue with staggered treatment and heterogeneous treatment effects, when the early-treated are used as a control group. This can lead to the estimator not only being biased but also having the opposite sign of the individual treatment effects because of negative weights. This negative weighting can arise because the early-treated control group has been treated and the treatment effect for the second period is differenced out by the DID estimator (de Chaisemartin and D'Haultfoeuille, 2022).

[4] I define tracts that are in the bottom 50% of the distribution of wildfire risk as low or medium wildfire risk, as scored by the Federal Emergency Management Agency (FEMA) in 2021.

years, there remains a 6.5 p.p. (18.5%) increase in the likelihood that an individual from a first-burned census block lives in a different census tract. However, though people living in census blocks hit by a wildfire are more likely to move to safe areas compared to those who are never burned, they remain less likely than if they were to move like the average mover in California, where 66% of all moves are to low- or medium-wildfire-risk census tracts. This suggests that people living in areas that are burned may prefer characteristics of the location that correlate with wildfire risk and select into these areas. Moreover, the adaptive migration effect dissipates to become statistically indistinguishable from zero in the longer term, four years after the fire.

To understand potential barriers to moving adaptively, I investigate who is more likely to move and why. In particular, I consider the role of financial constraints, which may prevent people from making their desired migration choices. Financial institutions may influence migration decisions by allowing individuals to borrow through loans or credit cards to make their preferred decisions. Individuals with higher credit scores generally have easier access to borrowing, which may exacerbate existing inequalities. Indeed, I find suggestive evidence that financial constraints impact adaptive migration: Although all individuals, regardless of credit score, have a similarly increased likelihood of moving after experiencing a wildfire, only those with high credit scores move to low- or medium-risk areas in the longer term. Moreover, those whose homes are damaged – and who thus are likely to receive an insurance payout shortly after the wildfire – are also more likely to move to safe areas.

Given this suggestive evidence of the importance of financial constraints, the government could, in theory, impact adaptive migration by providing aid to lessen liquidity concerns. If people are unable to move optimally because of credit constraints and aid increases liquidity, this can promote adaptive migration – as long as individuals want to move to lower-risk areas. On the other hand, the tying of aid to incentives to return to the damaged homes can hinder adaptive migration: Areas that burn are generally high-risk areas, and so remaining in the same location is not adaptive.

Estimating the impact of government aid is difficult because there are factors that simultaneously affect both aid receipt and migration. A simple comparison of the migration responses between individuals who experienced fires that receive government aid with those in fires that do cannot identify the causal impact of the assistance because areas that experience more severe fires – and thus larger displacement effects – are more likely to receive aid (GAO, 2020). Moreover, within an area that receives aid, not all individuals receive payment: The aid application process is onerous, opaque, and confusing (GAO, 2020). Applicants must provide extensive documentation before receiving aid, which has been criticized as a reason why some applicants who qualify for aid, particularly those from disadvantaged groups, are denied it (GAO, 2020; Billings et al., 2022).

To address this endogeneity concern, I leverage the fact that there are political incentives to provide assistance as an instrument to identify the causal impact of government aid. To unlock federal disaster assistance, which is disseminated through the Federal Emergency Management Agency (FEMA), the president must make a disaster declaration for the impacted county (FEMA, 2003). I discover that counties that are politically competitive – which I proxy by their having a margin of less than 5% between the top two vote shares in the most recent presidential election – are more likely to receive FEMA aid. This is consistent with the political science and economic history literature highlighting that politically competitive areas receive more government assistance (Wright, 1974; Fleck, 2001; Fishback et al., 2007; Reeves, 2011; Husted and Nickerson, 2014; Boustan et al., 2017; Jou and Morgan, 2024). Based on this insight, I implement this measure of political competitiveness as a novel instrument for aid receipt, which provides strong first-stage results in the instrumental variables (IV) strategy I employ to identify the causal impact of aid on adaptive migration.

In both the ordinary least squares (OLS) regression and the IV regression, which corrects for aid endogeneity, I find that individuals living in areas that receive aid after a fire are more likely to migrate than those who do not. The OLS results indicate that there is on average an 17.0 p.p. increase in the likelihood of an individual in an area that receives aid of moving to a different census tract after a first fire, with no migration effect for the fires for which aid is not distributed. Moreover, individuals in areas with first fires that receive aid are 5.5 p.p. more likely to move to a low- or medium-wildfire-risk census tract. The IV regression yields an even larger average estimate of the effect of aid on moving: a 33.0 p.p. increase. The difference between the IV and OLS estimates suggests that the latter suffers from downward bias, consistent with the conjecture that people who are more likely to migrate are the least likely to receive aid. The IV results indicate no effect of aid on moving to low- or medium-wildfire-risk areas, which could be because there are no adaptive location requirements for aid receipt. This suggests that although aid helps people move, the current implementation of aid does not promote adaptive migration.

This paper contributes to the literature in three ways. Previous work has found that, after the most destructive wildfires, there is an increase in out-migration probability in the short term, within the first two years after the event (Chase and Hansen, 2021; McConnell et al., 2021; Sharygin, 2021; Winkler and Rouleau, 2021; An et al., 2023; DeWaard et al., 2023; Hennighausen and James, 2023; DeWaard et al., 2024; McConnell et al., 2024).[5] There have been mixed evidence for other natural disasters: Some studies find hurricanes have little to no impact on county out-migration (Henkel et al., 2022; Behrer and Bolotnyy, 2023), while others find an increase in the propensity to leave the county (Sheldon and Zhan, 2022). Tracts with high risk of coastal flooding have significantly less population growth compared to other tracts within the county (Indaco and Ortega, 2023). My unique data allow me to follow individuals over time, so I can identify where they move at a sub-county level and determine whether the migration responses are adaptive and observe the effects over a longer period (i.e. four years later).[6] Knowing where people move is key because if individuals leave for other risky locations, the migration will not moderate the impact of climate change. My paper is also the first to investigate how migration changes depending on whether the individual's house was burned, their credit scores, and how often the area has burned, which has

[5]My results confirm the increase in out-migration that McConnell et al., 2021 find for the first two years after a destructive wildfire occurs.

[6]The sub-county level is important because there is substantial variation of risk within the county.

important implications since climate change is expected to make wildfires more common.

The second key contribution of this study is the finding that government aid has a null effect on adaptive migration. The migration literature has flagged the need to consider the way government policies influence location decisions in the United States (Jia et al., 2023). Studies have speculated about the importance of government involvement rationalizing the different migration responses to historical and current disasters (e.g. between Boustan et al., 2012 and Deryugina, 2017), by exploring changes in migration after the creation of FEMA (Boustan et al., 2017), and by documenting an increase in government investment and higher population growth for election-year hurricanes (Henkel et al., 2022). These papers do not explicitly link government aid and migration but rather document a positive correlation. A handful of papers study the direct impact on migration, though they focus only on specialized, small-scale programs (Gregory, 2017; Elliott and Wang, 2023). All the studies focus on hurricanes and study only migration, not whether individuals move adaptively. I contribute to this literature by providing causal estimates of the impact a large-scale government aid program has on adaptive migration in the context of wildfires, using a novel instrument.

Finally, this paper offers insight into the dynamic spatial equilibrium model literature on long-run climate adaptation by shedding light on who adaptively migrates, and it proposes new dimensions to be incorporated. In particular, I highlight the importance of financial constraints in influencing how people move because I find that those least likely to be constrained (i.e. those with high credit scores) are more likely to adaptively migrate. Existing models typically model climate change as a shock to capital depreciation, amenities, and productivity (Desmet and Rossi-Hansberg, 2015; Desmet et al., 2021; Bilal and Rossi-Hansberg, 2023; Cruz and Rossi-Hansberg, 2023; Hsiao, 2023; Desmet and Rossi-Hansberg, 2024) and need to make simplifying assumptions for tractability. My results suggest that incorporating financial constraints is important because the policy implications differ depending on how preferences and constraints impact migration choices. They also suggest that including government intervention into these models would be fruitful because aid can be a means of addressing liquidity constraints and repairing existing amenities or capital (as modeled in Henkel et al. (2022), though they abstract from capital destruction). Including different forms of government aid into these models would elucidate which policies can be most effective for addressing climate change.

This paper is related to the literature on climate adaptation. There is a broad literature that studies the impact of long-run changes implemented in response to trends in climate or the environment (Dell et al., 2014; Annan and Schlenker, 2015; Hsiao, 2023; Bento et al., 2023a; Bento et al., 2023b). Although the riskiness of an area can be known, most areas – even those with the highest wildfire risk – will not burn in a given year, and thus experiencing a fire could be viewed as an unexpected event, especially in my empirical setting in which I compare individuals who are in blocks that burned for the first time. People may have limited ability to adapt to unexpected shocks, which is consistent with my finding that financial constraints prevent people from moving. However, people have more time to adjust to long-run climate changes. Nevertheless, my paper is relevant to this literature because migration is a rare outcome and even in this situation where people are forced to move due to a shock that brings climate change to mind, they are not moving to safe areas. Thus, it is unlikely to expect adaptive migration to substantially minimize the costs of natural disasters.

The rest of the paper is organized as follows. Section 2 describes the background, including the California wildfire landscape and how government aid is disbursed, and outlines factors that impact people's migration decisions. Section 3 details the data used in this analysis, and section 4 explains the empirical strategy. Section 5 presents the main migration results. Section 6 explores the role of aid and presents a causal analysis on federal FEMA aid receipt. Section 7 concludes, offering an overview of adaptive migration and offering potential explanations for why it is not occurring, as well as directions for future research.

2 Background

2.1 Wildfires and Migration Conceptual Framework: Preferences vs. Constraints

Individuals consider a multitude of factors in deciding where to live. If governments seriously consider adaptive migration a promising strategy for minimizing the impact of natural disasters, understanding how individuals make migration decisions is key for designing policies that promote it. Three factors influence whether adaptive migration occurs: moving costs, preferences, and constraints. First, individuals need to overcome the moving costs. Next, for individuals to choose to move adaptively, they must both want to (i.e., have a preference for it) and be able to (i.e., be able to afford to live in safe areas). If individuals want to move to safe areas but cannot afford to (i.e., they are financially constrained), monetary assistance through disaster aid could increase adaptive migration. However, if they want to stay in the area, then aid may not lead to adaptive migration. Additionally, requirements attached to the aid can incentivize certain behaviors. Thus, differentiating between preferences and constraints is crucial for designing effective policies.

I construct a simple location choice model to guide the discussion about how wildfires can interact with individual preferences and financial constraints to influence migration decisions. Assume each location l has exogenous amenities (A_l), rents (R_l), and wages (w_l). I also include an individual-level utility derived from enjoying their home, which can grow over time ($h^i_{l,t}$). Let the indirect utility of location l at time t be determined by the location characteristics and home value: $U_{l,t} = w_{l,t} + A_{l,t} - R_{l,t} + h^i_{l,t}$. To allow heterogeneity among individuals in their valuation of a location, let individual i draw an idiosyncratic location preference shock each period t across all locations, and the shock for location l is denoted as $\epsilon^i_{l,t}$. I also include the option value of staying in the location next period ($\beta\mathbb{E}[V^d_{t+1}]$), which is the discounted *ex-ante* expected amenities, rents, wages, and home value next period.

Wildfires can impact a location in several ways. If a disaster occured in time t, this impacts the amenities, rents, and wages for the burned location in the next period $(t+1)$, which would be unchanged otherwise. Suppose location l experiences a wildfire at time t so that the subscript pair l, t represents location l at time t and $l, t+1$ is location l the period after the wildfire occurred. The disaster will decrease the location's amenity value $(A_{l,t+1} < A_{l,t})$, such as by destroying local infrastructure or marring the view. However, there is evidence that the housing cost of the location decreases after a wildfire $(R_{l,t+1} < R_{l,t})$ (Contat et al., 2024).[7] There have been mixed results about how local wages change after a disaster $(w_{l,t+1} \lesseqgtr w_{l,t})$ (Belasen and Polachek, 2009; Groen et al., 2019; Lapinski et al., 2025). There could also be changes in the probability of a wildfire occurring in the area $(Pr(f_{l,t+1}) \lesseqgtr Pr(f_{l,t}))$ and the probability of an individual's home being damaged if a wildfire occurs $(Pr^i(f^i_{h,t+1}|f_{l,t+1}=1) \lesseqgtr Pr^i(f^i_{h,t}|f_{l,t}=1))$. For instance, if an area has just burned, the short-term risk of a wildfire decreases because there is no fuel for a fire (Farkhondehmaal and Ghaffarzadegan, 2022). However, the fact that the area has burned reveals its potential to burn again, so the long-term risk may increase. In addition, individuals may update their beliefs about the riskiness of the area based on their experience with the wildfire.

The option value can be rewritten to incorporate the expected changes, which depend on whether a disaster occurs in location l or not. With probability $Pr(f_{l,t})$, the location characteristics change and the indirect utility is: $w_{l,t+1} + A_{l,t+1} - R_{l,t+1} + h^i_{l,t+1} - Pr^i(f^i_{h,t}|f_{l,t}=1)q^i_{l,t}$. With probability $1 - Pr(f_{l,t})$, the location characteristics do not change between time t and $t+1$ and the indirect utility is: $w_{l,t} + A_{l,t} - R_{l,t} + h^i_{l,t}$. The *ex-ante* expected value of location l for time $t+1$ can thus be written as:

$$\begin{aligned}\mathbb{E}[V^d_{t+1}] = {} & w_{l,t} + A_{l,t} - R_{l,t} + h^i_{l,t} \\ & + Pr(f_{l,t})[(w_{l,t+1} - w_{l,t}) + (A_{l,t+1} - A_{l,t}) - (R_{l,t+1} - R_{l,t}) - Pr^i(f^i_{h,t}|f_{l,t}=1)q^i_{l,t}]\end{aligned}$$

Every period t, the individual i in location l receives the idiosyncratic location shock draws $(\epsilon^i_{d,t})$ and chooses a destination d – which may be the same as her starting location l – and executes the move and pays the moving cost $(m^{l,d}_t)$. Next, the destination d will draw f_d and f^i_h, which determines whether a disaster happens in location d and whether individual i's specific home is damaged, respectively. This also determines the characteristics for the next period $(t+1)$. After the disaster, there will be a draw on whether individual i receives post-disaster payment (g^i_h). Once the disaster occurs, the individual realizes the preference shock $(\epsilon^i_{d,t})$, and then works and consumes

[7] A recent review of the climate and real estate literature finds a negative effect on home prices after a wildfire (Contat et al., 2024). This change could be positive through raised insurance premiums, though in California there is a moratorium that does not allow insurers to increase their premiums the year after a disaster declaration (CDI, 2021). Moreover, in the immediate aftermath, there could be a steep decrease in local housing supply from the fire destruction, and if people are trying to stay nearby to oversee the damage assessment process, rental costs can be expected to be higher. This conjecture is corroborated by anecdotal evidence (Bittle, 2023). In the longer term, Issler et al., 2020 find that housing prices actually rise, and they hypothesize this is because destroyed homes are rebuilt and now follow higher safety code requirements, justifying the higher price. Thus, depending on the time period of interest, the housing cost could increase or decrease. I assert that prices decrease because the housing prices decrease in the six quarters after the wildfire (An et al., 2023), before rebuilding can take place, and the decision to rebuild is likely made after deciding to leave or to stay.

in the chosen location d given the budget constraint until the end of the period.

I allow individuals to anticipate their ability to make migration decisions in future periods and the future utility obtained from different locations so they make forward-looking migration decisions, which include a moving cost ($m^{l,d}$) defined for those who start in location l as 0 if she stays in the same location ($l = d$) and some positive $c^{l,d}$ if she moves ($l \neq d$). Individuals are subject to a budget constraint each period t, in which the individual's savings (S_t^i), wages ($w_{d,t}$), and any post-disaster payment ($\mathbb{1}[g_{h,t}^i = 1]I_{h,t}^i$) can cover the rental ($R_{d,t}$) and moving costs ($m_t^{l,d}$): $S_t^i + w_{d,t} + \mathbb{1}[g_{h,t}^i = 1]I_{h,t}^i \geq R_{d,t} + m_t^{l,d}$. I assume that each individual i's initial level of savings S_0^i is exogenously drawn, and they make their first location choice given that amount. The savings for the next period ($t+1$) follow a deterministic function based on what is not used up by the end of the current period (t), which is based on the characteristics of the location, whether the individual's home is damaged, whether the individual receives post-disaster payment, and whether the individual chooses to move from l to d: $S_{t+1}^i = S_t^i + w_{l,t} - R_{l,t} - m_t^{l,d} + \mathbb{1}[g_{h,t}^i = 1]I_{h,t}^i$. Let $\beta\mathbb{E}[V_{t+1}^l]$ represent the option value of choosing l, which includes the *ex-ante* expected value for location l in the next period ($\mathbb{E}[V_{t+1}^l]$) and the discount rate (β).

$$\max_d \left\{ \underbrace{w_{d,t}}_{\text{Wage}} + \underbrace{A_{d,t}}_{\text{Amenity}} - \underbrace{R_{d,t}}_{\text{Rent}} + \underbrace{\beta\mathbb{E}[V_{t+1}^d]}_{\text{Option value}} + \underbrace{\epsilon_{d,t}^i}_{\substack{\text{Idiosyncratic} \\ \text{shock}}} - \underbrace{m_t^{l,d}}_{\text{Moving costs}} \right\}$$

$$\begin{aligned} &\text{subject to } S_t^i + w_{d,t} + \mathbb{1}[g_{h,t}^i = 1]I_{h,t}^i \geq R_{d,t} + m_t^{l,d} \\ &\text{and } S_{t+1}^i = S_t^i + w_{d,t} - R_{d,t} - m_t^{l,d} + \mathbb{1}[g_{h,t}^i = 1]I_{h,t}^i \\ &\text{where } \begin{cases} g_{h,t}^i = 1 & \text{Received post-disaster payment} \\ g_{h,t}^i = 0 & \text{Did not receive post-disaster payment} \end{cases} \end{aligned}$$

The location changes after the disaster: Although the amenities decrease ($A_{l,t+1} < A_{l,t}$), the rents also decrease ($R_{l,t+1} < R_{l,t}$) and the wages and the probability of a disaster, and subsequently the location's option value for the next period, may also change ($|w_{d,t+1} - w_{d,t}| \geq 0$ and $|\beta(\mathbb{E}[V_{t+1}^d] - \mathbb{E}[V_{t+2}^d])| \geq 0$). There can be an additional utility loss if the individual's home is destroyed: $h_{l,t+1}^i \leq h_{l,t+1}^i$. Since the wildfire occurs after the individual has chosen their initial location l in time t, the indirect utility in location l for time $t+1$ will differ from that of time t:[8]

$$\underbrace{(A_{l,t+1} - A_{l,t})}_{<0} + \underbrace{(w_{l,t+1} - w_{l,t})}_{\lesseqgtr 0} + \underbrace{(h_{l,t+1}^i - h_{l,t}^i)}_{\leq 0} \overset{?}{\lesseqgtr} \underbrace{(R_{l,t+1} - R_{l,t})}_{<0} + \underbrace{\beta(\mathbb{E}[V_{t+1}^d] - \mathbb{E}[V_{t+2}^d])}_{\lesseqgtr 0}$$

Depending on how these characteristics of the location interact, people may choose to move or to

[8]This is also seen in the option value for the next period, which incorporates the expectation of whether a disaster will happen or not and how it will impact the location.

stay. People would choose to stay in the current location even though it burned if the decrease in amenities and home value and the change in the wages are less than the decrease in rents and the change in option value (i.e., $(A_{l,t+1} - A_{l,t}) + (w_{l,t+1} - w_{l,t}) + (h^i_{l,t+1} - h^i_{l,t}) \leq (R_{l,t+1} - R_{l,t}) + \beta(\mathbb{E}[V^d_{t+1}] - \mathbb{E}[V^d_{t+2}])$) and the moving cost to move the next period is larger than the difference of the expected indirect utility between locations (i.e., $m^{l,d}_{t+1} \geq \mathbb{E}[U_{d,t+1}] - \mathbb{E}[U_{l,t+1}]$). People would choose to move to location l if the decrease in wages, amenities, and home value are greater than the decrease in rents and the change in option value (i.e., $(A_{l,t+1} - A_{l,t}) + (w_{l,t+1} - w_{l,t}) + (h^i_{l,t+1} - h^i_{l,t}) > (R_{l,t+1} - R_{l,t}) + \beta(\mathbb{E}[V^d_{t+1}] - \mathbb{E}[V^d_{t+2}])$) and if the moving cost is less than the difference of the expected indirect utility between locations (i.e., $m^{l,d}_{t+1} < \mathbb{E}[U_{d,t+1}] - \mathbb{E}[U_{l,t+1}]$). Thus, people may move or stay depending on their preferences.

Financial constraints may also prevent individuals from moving adaptively. People make their location choice given their budget constraint: $S^i_t + w_{l,t} + \mathbb{1}[g^i_{h,t} = 1]I^i_{h,t} \geq R_{l,t} + m^{l,d}_t$. Having financial resources (i.e., higher savings (S^i) and wages (w_l)) provides more options to the individual by helping them afford higher rents (R_l) and to pay the moving costs ($m^{l,d}$). Receiving post-disaster payment (i.e., $g^i_{h,t} = 1$), such as in the form of insurance payouts or government aid, also increases financial resources.

Financial constraints can be conceptualized as liquidity and solvency constraints. Liquidity constraints are when people are presently unable to pay an amount, though they could eventually over their lifetime using their expected earnings. If people want to move but they cannot pay the initial moving cost, this could be due to a liquidity constraint. Solvency constraints, on the other hand, are when people are unable to afford a payment because it is larger than their lifetime expected earnings. Areas that are low wildfire risk are also more expensive (i.e., $Pr(f_l)$ is negatively correlated with R_l).[9] Individuals may not be able to afford the housing costs to live in safe areas, which is a solvency constraint. There are large financial costs that are incurred because of a disaster: People could close their jobs or see their working ability restricted, especially if they were evacuated. Individuals could initially choose to move to a safe area but, as they deplete their savings, choose to move to cheaper areas, which happen to also be at higher wildfire risk. Both types of financial constraints could prevent people from moving adaptively even if they want to.

Wildfires force individuals to assume the fixed costs of moving and reoptimize their location choices. As they are forcibly displaced in the short term through mandatory evacuations or their dwellings burning, people may make their location choice as if they did not face moving costs. In addition, individuals may prefer to live in areas with features that are positively correlated with wildfire risk – that is $Corr(A_l, r_l) > 0$ – such as proximity to nature or pleasant views (Hammer et al., 2009; Winkler and Rouleau, 2021). Individuals with such preferences may choose to return to the burned area or move somewhere else with high wildfire risk – that is migration, even when it occurs, may

[9] Using house price index data from the Federal Housing Finance Agency (FHFA) and wildfire risk data from FEMA, I find that there is a negative, statistically significant correlation between the two. The relationship holds for the United States overall and for California specifically (Table B1).

not be adaptive.

This conceptual framework shows how, in theory, government interventions could facilitate or hinder adaptive migration, depending on how aid is disbursed. First, the government could improve the amenities of the location by restoring infrastructure ($A_{l,t+1} \geq A_{l,t}$) or increase wages by revitalizing the local economy ($w_{l,t+1} \geq w_{l,t}$). This is unlikely to encourage adaptive migration because it increases the value of the burned location compared to alternative destinations.[10] Second, the government could give a one-time transfer ($I^i_{h,t}$ because $g^i_{h,t} = 1$) to individuals impacted by the disaster. This could facilitate adaptive migration if the fixed moving cost is the main barrier to migration because this transfer could help people overcome their liquidity constraints. However, this one-time transfer would not lead to adaptive migration if people prefer high-risk areas for the amenities or idiosyncratic location preferences. Moreover, even if the one-time transfer helped individuals move to safe places initially, this type of aid would not facilitate long-term adaptive migration if people are solvency constrained and cannot afford the increased cost of living in the safe locations: that is, $I^i_{h,t} + S^i_t + w_{l,t} \geq R_{l,t} + m^{l,d}_t$ but $S^i_{t+n} + w_{l,t+n} < R_{l,t+n}$ after n time periods. Finally, the government could give location-specific aid. One example of such aid could be providing job search assistance or longer-term transfers to low-risk areas. This should lead to increased adaptive migration if the barrier is primarily a solvency issue, but again might not if the migration decision is driven solely by preferences.[11] Another example of location-specific aid could be home repair aid, which should not facilitate adaptive migration as people are incentivized to return to the burned areas, which are typically high-risk locations. The characteristics of California insurance coverage landscape also interact with the amount of aid individuals receive, further complicating the migration decision.[12] For instance, people whose homes are damaged are likely to receive insurance payouts, which can also be conceptualized as $I^i_{h,t}$ and loosen the budget constraint. Thus, government aid can make adaptive migration more or less attractive depending on the way it is implemented.

2.2 California Wildfires

There has been an increase in wildfires in California over the past three decades, as can be seen in Figure 1. The past decade saw a dramatic increase in the most severe fires, megafires, which burn over 100,000 acres. Since 1990, on average, there have been almost 20 additional fires every year.

Wildfires in California are concentrated in certain geographic areas. Some locations are at higher risk of wildfires because of the environmental landscape, vegetation, slope, and wind direction (B. M. Collins et al., 2007; B. Collins et al., 2009; Thompson and Spies, 2009; Estes et al., 2017; Rao et al.,

[10] There is suggestive evidence that this phenomenon occurs after hurricanes (Deryugina et al., 2018; Henkel et al., 2022).

[11] The amount given could sway individuals who are indifferent between the safe and risky areas. Given that the amenity differences between these types of locations are stark (i.e. different environmental landscapes), depending on the monetary amount, there may not be many people switching to safe areas.

[12] FEMA explicitly states that it is not a substitute for insurance. It can cover costs that insurance does not, though it requires a copy of insurance settlement about the damage (FEMA, 2023).

2022). These factors can be used to create fire hazard ratings for a given area, such as the fire hazard severity zone classification published by the California Department of Forestry and Fire Protection (CAL FIRE) and FEMA's wildfire risk scores. Although wildfire incidence within a given location is cyclical in the short term because the fire destroys vegetation and brush, which limits fuel for a wildfire in the immediate future (Farkhondehmaal and Ghaffarzadegan, 2022), many factors that contribute to wildfire risk are immutable. Thus, areas that have previously burned may burn again: the map in Figure 2(a) highlights where California wildfires burned in the 2000s, 2010s, and the early 2020s.

Even as certain areas burn again over time, the majority of areas that burn do so for the first time. From 1950-2021, almost 60% of all of the census blocks that burned did so just once, with approximately 20% of the burned census blocks burning more than three times during this period, as can be seen in Figure 2(b). Climate change is changing the landscape such that certain areas will have an increased risk of burning for the first time, and the likelihood of severe burns will also rise (Goss et al., 2020).

Although California is particularly prone to fires, its burning trends are similar to those in other parts of the United States and the world. It is well documented that there is increased and more severe wildfire activity across the western United States (Westerling et al., 2006; Dennison et al., 2014; Mueller et al., 2020; Donovan et al., 2023). In addition, the eastern United States (Donovan et al., 2023) has experienced substantial building into undeveloped wildland in recent decades, so there is a growing population that will be potentially impacted by wildfire risk (Radeloff et al., 2018). Globally, approximately 30% of the world surface is prone to frequent wildfires, and the number and the severity of these events are increasing over time (see Goncalves and Vieira (2015) for a review). Thus, the scope of the question of how people respond to growing wildfire risk extends beyond California and has global relevance.

2.3 Government Aid

After a natural disaster, government aid – ranging from short-term housing assistance to long-term reconstruction loans – is mobilized to help the impacted individuals. FEMA is the national provider of aid and administers all federal-level assistance (FEMA, 2023). To activate FEMA, the US president must issue a disaster declaration, a power exclusive to the president and not requiring the approval of Congress. Typically, albeit not necessarily, the process of disaster declaration issuance begins with a request from the state governor, which includes documentation that the state's resources are insufficient to ameliorate the situation. The state must provide an initial assessment of the extent of damage, which FEMA-appointed inspectors will confirm, and the FEMA regional administrator will present a recommended plan of action to the president. Once the president declares a disaster for a county, FEMA is approved to mobilize workers and start the application process whereby individuals can receive grants (FEMA, 2003).

Because this paper focuses on individual adaptive behavior, I examine FEMA's Individuals and Households Program (IHP), the most prevalent form of assistance, whereby financial assistance is provided directly to individuals to address disaster-induced needs.[13] The IHP provides grants for individuals to assist with immediate needs, such as rent, living expenses, and medical costs, as well as grants to rebuild or repair damaged property. I calculate that, across 2014-2024, FEMA spent $13.9 billion in IHP aid, with $319 million for California and $169 million specifically for California wildfires.[14]

In order to receive FEMA assistance, individuals must first choose to apply for specific types of aid, which reflects their preferences, and be approved for that aid, which depends on the verification process. Applications for FEMA assistance require a series of background checks and submission of approved documentation. Some of the eligibility checks include citizenship status, identity confirmation through a valid Social Security number (SSN), ownership or occupancy verification, and insurance status (FEMA, 2023). This information is often validated automatically through public records databases.[15] Applicants can appeal FEMA's decision or the amount of assistance received within 60 days of decision notification.(FEMA, 2023).

The two largest components of the IHP are rental aid and home repair aid. People who want to move away can apply for rental aid, which could help ease their transition to a new living place. There is also aid specifically for moving expenses.[16] Rental assistance is available for people unable to live in their homes because of direct housing damage or surrounding damage to infrastructure (FEMA, 2024a). It is intended to cover temporary housing for one to two months, and extensions up to 18 months can be requested. This funding can be used to cover rent in any location, though the amount is based on the US Department of Housing and Urban Development's calculation of the Fair

[13] Another individual-level government program is the Small Business Administration (SBA) loans program, which extends loans of up to $500,000 on highly desirable terms for individuals to rebuild their homes. I have not yet incorporated this type of assistance into my analysis. However, application for any type of federal disaster assistance requires an initial FEMA application (FEMA, 2023). FEMA has several other programs to assist local governments. It utilizes three forms of disaster aid: individual assistance (IA, which subsumes the IHP program studied in this paper), public assistance (PA), and hazard mitigation assistance (HMA) (CRS, 2024). I abstract from non-individual assistance, though higher-level aid could impact the desirability of a location as individuals make their migration decisions. Indeed, Henkel et al. (2022) argue that post-disaster government reconstruction improves the area's amenities, boosting the county-level population after a hurricane.

[14] This calculated amount is similar to the amount that the GAO calculated for the FEMA budget between fiscal years 2004 and 2013: $95 billion total, with $25.9 billion for individual assistance, $12.7 billion for overhead, $6.1 billion for mission assignment, and $5.2 billion for hazard mitigation (Lunney, 2014). Individual assistance accounts for 27% of the overall FEMA disaster relief fund.

[15] The IHP grant application process has been criticized as inaccessible, especially for disadvantaged individuals. The US Government Accountability Office (GAO) has found that FEMA has often denied IHP claims for inadequate documentation, such as proof of residency, extent of damages, and insurance status. In the face of concerns over fraudulent claims, FEMA's approval rates have fallen drastically over time. Though applicants can contest denials, the appeals process is convoluted, often incomplete, and difficult to understand, "requiring a reading level of a high school senior" (GAO, 2020), which could disproportionately exclude those with lower education and income. FEMA automatically scans public records databases and rejects applications in which the applicant is not found to own their home. Low-income and minority households are more likely to rely on more informal inheritance norms so that the heir was bequest the home but does not have the required paperwork necessary to prove ownership. In 2024, in response to the GAO report and other criticisms, FEMA updated its grant application process (FEMA, 2024b).

[16] Moving expenses are counted under the broad "other needs assistance" category of aid (FEMA, 2024a).

Market Rent of the burned area.[17] A disaster declaration that unlocks federal aid could help people who want to move to migrate, leading to higher migration out of the burned areas. Conversely aid to repair damaged property could help people who want to stay in the area rebuild their homes, decreasing out-migration. The maximum amount of financial assistance for home repairs is adjusted annually, and in 2024, it was $42,500, though this does not include rental costs (FEMA, 2024b). This could help people who want to stay in the area to rebuild their homes, decreasing migration from the area. From 2002 to 2024, the average amount of aid received in a county for a given wildfire disaster for homeowners was $61,440, with $37,859 dedicated to repair and replacement aid, $7,661 to short-term rental assistance, and $13,875 to other needs. Renters received $39,094 on average in total, with $6,109 for rental assistance and $31,784 for other needs.[18] Thus, receiving a disaster declaration and unlocking federal aid could theoretically facilitate or hinder migration.

3 Data

To explore how individuals use migration, financial institutions, and government aid after experiencing a fire, I use detailed location and credit data to assess the extent of adaptive migration, that is, moves from risky to safe areas.

3.1 Fire

I use data from the California Department of Forestry and Fire Protection (CAL FIRE) to define the census blocks that are burned. Responsible for California's fire suppression efforts, CAL FIRE keeps careful and complete records of wildfires within the state. I merge shapefiles of perimeters of wildfires from 1950 to 2021 with maps to identify which census blocks were affected by wildfires. I define the fires at the census block-level because this is the finest geographic unit for which credit data are available. A census block is smaller than a census tract, which is in turn smaller than a county; at the time of the 2010 census, there were 710,145 census blocks, 8,057 census tracts, and 58 counties in California (Bureau, 2021).[19] I can also calculate the percentage of the block that is burned as a measure of the intensity of fire damage at block level.

I can also identify which houses within a census block were damaged. I obtain address-level data of damaged properties from CAL FIRE that span 2013-2021, and I separately identify the migration effects based on the extent of wildfire damage.[20] CAL FIRE damage inspection specialists (DINS)

[17] From conversations with FEMA officers, the intent of the rental aid is to help individuals remain nearby to minimize the impact on their employment and oversee the rebuilding process.

[18] These numbers are winsorized at 1% at each tail by disaster and beneficiary type (homeowner vs. renter).

[19] I list the categories for the 2010 census because the credit data defines locations using this census. The US Census Bureau defines these census geographies in order to create statistical areas bounded by "visible features such as roads, streams, and railroad tracks, and by nonvisible boundaries such as property lines, city, township, school district, county limits and short line-of-sight extensions of roads" (Rossiter, 2011). Census tracts have an ideal population of 4,000 people (Bureau, 2022). Half of the census blocks within the United States are smaller than a tenth of a square mile (Lynch, 2020).

[20] The dataset has recently been updated to include damaged properties up to 2023. It has been used in other papers, such as Baylis and Boomhower (2021) and Biswas et al. (2023).

complete assessments on damaged properties, in which a team of three or four people perform a walk-around of the property to identify any damage and complete a damage assessment report if any is found (NIST, 2019). The majority of the damaged buildings are characterized as "destroyed ($> 50\%$)" burned, though they can also experience "major ($25 - 50\%$)", "minor ($10 - 25\%$)", and "affected ($< 10\%$)" damage. The data also include addresses without damage, "no damage."[21]

3.2 Wildfire Risk

To determine whether individuals move from risky to safe areas, I use FEMA's wildfire risk index to measure the fire danger of the census tract in which the person lives after the fire. FEMA provides a national risk index of natural disasters for each state at the census tract level for a variety of climate shocks, including wildfires.[22] The data are from 2021 and are applied retrospectively, representing an *ex post* wildfire risk score. The wildfire risk score ranges from 0 to 100, and I classify a tract as low risk if it's between 0-25 and low or medium risk if it's between 0-50. I define a move as adaptive if the person appears in the data in a low- or medium-risk tract. The wildfire risk score for the United States approximately follows a uniform distribution (Figure A1(a)), while that for California has a large percentage (over 60%)ß of tracts that are low risk and a slight overrepresentation at the highest part of the risk distribution (Figure A1(b)).[23]

3.3 Migration

To measure migration, I use two complementary datasets, which yield similar migration rates. Each offers specific advantages and disadvantages, and so when taken together, they paint nuanced picture of how people move after they experience a wildfire.

The University of California Consumer Credit Panel (UCCCP) used in this analysis includes credit and demographic data for a longitudinal panel of everyone who has ever lived in California and has a credit record. The data have consistent census block information from 2014-2021.[24] There are approximately 40 million consumers. The data include household members and cosigners as well as their location at the zip code and census block level. They also include demographic information about the consumers (including race, gender, age, education, and occupation), credit scores, and raw

[21] The "no damage" is recorded beginning in 2018 (CalFire, 2024).

[22] Other measures include the expected annual loss (EAL) to individual natural disasters and the overall risk, which combines the EAL, social vulnerability, and community resilience measures.

[23] There is a large mass of census tracts that are bunched at 0 risk. For the overall US distribution, approximately 25% of all tracts have a risk score below 25. For the California distribution, approximately 60% of all tracts have a risk score of 0, so many locations within the state have low risk. However, there is also a large mass at the highest risk level and underrepresentation at the middle risk levels.

[24] The data span 2004-2023, but the census block designation changes from the 2000 census definition of blocks for 2004-2014 to the 2010 census definition for 2014-2021 and to the 2020 census definition for 2021-2023. Even when using crosswalks between the different definitions to standardize, I see a spike in migration in years where the census designation changes. This is because there is not a clean mapping across the censuses' characterization of areas: Some census blocks split into smaller entities, while others are combined. There are also higher rates of missingness for census blocks before 2010. Thus, for ease of analysis, I restrict my sample period to 2014-2021, which also coincides the occurrence of many large fires.

tradeline-level information about each loan or collections item (including payment history, credit limits and balances, mortgage delinquency, and foreclosure). This dataset also allows me to measure mobility since I can construct a move based on whether the individual is in a different block from the previous quarter.

Because the dataset covers people with a credit history, the population may be older and wealthier than the general population. I conduct validation exercises and find that the migration rates and population coverage are similar to those of the census and the American Community Survey (ACS).

Infutor is an address-level, commercial dataset of adults that spans 1990-2022. It tracks an individual's ten most recent United States residences and, importantly, includes verification of the residence, ensuring that at least two pieces of documentation confirm an individual's being at the location before it is added to the dataset. A subset of the Infutor data includes the individual's birthdate, which can be used to calculate her age, and the duration of time the individual is seen at an address, both important correlates of mobility. The data also sometimes include the individual's gender and social security number (SSN).

My use of both the UCCCP and Infutor data provides a richer understanding of migration. The UCCCP data provide detailed demographic information that makes it possible to conduct heterogeneity analyses about which groups migrate. In particular, they offer insight on the extent of differential migration responses based on access to financial institutions (proxied by credit score). The main disadvantage of the UCCCP data is that I cannot directly observe whether an individual's home is damaged by the fire as I do not have address-level data. The time coverage (2014-2021) also restricts the horizon of analysis for long-term migration results; to have adequate power and assess pretrends, I present outcomes up to four years after the disaster using the UCCCP data.

The Infutor data supplement the UCCCP analysis because they include the exact address and follow individuals over a longer period (1990-2021), specifically addressing UCCCP's limitations. However, Infutor has much less detailed demographic information, and its linkage algorithm is opaque. Nevertheless, the estimates of the increase in migration probabilities after a wildfire calculated across both datasets are similar.

3.4 Government Aid

FEMA offers aid for individuals and households impacted by presidentially declared natural disasters through the Individual and Households Program (IHP). This program provides grants for various purposes, including short-term rental assistance – which can be used in any location – and rebuilding grant – which is used to repair damaged homes. These data are publicly available at the geographic level, though the finest geographic unit is the zipcode, which is substantially larger than a census block, the level at which I define the fire treatment.[25] I define aid as an indicator of whether a

[25] Census tracts, which are larger than census blocks, are typically around 4,000 individuals, whereas zipcodes are constructed by the U.S. Postal Service to coordinate mail delivery and have on average 10,000 individuals (Bureau,

zip code received any IHP aid and categorize fires on the basis of which ones received any aid and which did not.

4 Empirical Strategy

To quantify whether people move as a result of a fire, I conduct a stacked difference-in-differences (DID) event study, which relies on the identifying assumption that the trajectories of those in treated and control blocks would be parallel, but-for the fire.

4.1 Stacked Difference-in-Differences Event Study

To assess the impact of a wildfire on migration, I conduct a stacked difference-in-differences event study, which compares the outcomes of people living in census blocks that are burned for the first time with those living in never-burned blocks within the same tract before and after the fire. This is a stacked regression because I take multiple fire experiments and standardize the time variable to be relative to when the fire occurred, which I define as time 0 ($r = 0$). By using this design, I can take advantage of multiple fire events and obtain greater power for my estimates.[26]

I estimate the following regression equation:

$$y_{i,f,t} = \mu_i + \sum_{r=-3,\neq-1}^{N=4} \lambda_{r(f,t)} + \sum_{r=-3,\neq-1}^{N=4} \beta_r \lambda_{r(f,t)} \times fire_{b(i,f)} + \gamma_t + X_{i,t}^{'}\Gamma + \epsilon_{i,f,t} \tag{1}$$

The outcome variable ($y_{(i,f,t)}$) is defined for individual i at calendar time t and for fire f.[27] I include fixed effects for the individual (μ_i) to remove time-invariant individual-level factors.[28]. I have relative time $\sum \lambda_r(f,t) = \sum \mathbb{I}[t - E_f = r]$ fixed effects, spanning from three years prior to four years after the fire and omitting the year before the fire as the reference year. Each term ($\lambda_r(f,t) = \mathbb{I}[t - E_f = r]$) is equal to one when it is r years from the year when the individual i experienced fire f, which is denoted as E_f. The fire variable ($fire_{b(i,f)}$) is an indicator variable equal to one if the individual i lives in a census block ($b(i,f)$) that is burned for the first time by

2022; Bureau, 2023).

[26] If there are multiple blocks that burn for the first time at different years within a tract, I duplicate the control blocks for each of those fire events so that the burned blocks each get a set of controls and relative years defined by the year of the fire.

[27] In my main specification, each individual who lives in a census block burned for the first time in my sample is represented one time. However, there are cases where an individual could live in a never burned block that serves as the control group for multiple fire events. This would happen for tracts that have different blocks within it that burn for the first time across different years. In those cases, following the stacked difference-in-differences literature, I would duplicate the observation, and so the same calendar year t and individual i data would serve as a control across two fires, f_1 and f_2 (Wing et al., 2024). Thus, the data is unique at the individual, fire, and calendar year level.

[28] The individual fixed effects absorb the treatment fixed effects that are typical in this literature because the individual-level is more granular than the block-level, which is the level that the fire treatment is defined.

fire f and equal to zero if she lives in a never-burned census block within the same census tract.[29] The coefficients of interest are β_r, which capture how much the experience of the fire impacts the individual r years relative to the time of the fire. I normalize the difference between the treated and the control to be the year before the fire (event time -1). Because the fire is defined at the census block level ($b(i, f)$), I cluster standard errors at the block level (Abadie et al., 2023).

For robustness, I include calendar year fixed effects (λ_t) to control for general migration trends over time. I include potentially time-varying controls ($X_{i,t}$) for the age category, marital status, whether the individual completed college, and the duration of time that individual i lived in her census block ($b(i, f)$) at the time of the fire because these variables are found to be associated with migration.

To address the "forbidden comparison" concerns raised in the recent DID literature – namely, that bias may arise from including units that are eventually treated within the untreated group – (Callaway and Sant'Anna, 2021; Baker et al., 2022; de Chaisemartin and D'Haultfoeuille, 2022; Roth et al., 2023), my main specification investigates the responses of individuals in places burned for the first time and compares them with those of people living in never-burned blocks. Forbidden comparisons are an issue in the context of staggered treatment and heterogeneous treatment effects, when the early-treated are used as a control group, which can yield estimates that are not only biased but even have the opposite sign of the individual treatment effects. This is because negative weights can arise if the early-treated control group has been treated and the treatment effect for the later period is differenced out by the DID estimator (de Chaisemartin and D'Haultfoeuille, 2022). My results are robust to the use of other control groups, such as those living in blocks within a one-mile radius of the fire and those living in blocks one to five miles away from the fire.

I also estimate the DID version of Equation 1:

$$y_{i,f,t} = \mu_i + \nu post_{f,t} + \beta post_{f,t} \times fire_{b(i,f)} + \gamma_t + X_{i,t}^{'}\Gamma + \epsilon_{i,f,t} \tag{2}$$

In Equation 2, I compress the relative year fixed effects terms, $\sum \lambda_r(f, t) = \sum \mathbb{I}[t - E_f = r]$, into an indicator $post_{f,t}$ which equals one if year t is after the year when fire E_f occurred: $t - E_f > 0$. The coefficient of interest β captures the average of the impact of the fire at any point after the treatment.

4.2 Definitions of Terms

I define the fire treatment in two ways: 1) by whether a block is burned for the first time; and 2) by whether the block experiences a megafire (one that burns over 100,000 acres). With global warming, areas not previously burned are expected to experience a wildfire, and wildfires are expected to become more severe. I use these definitions of fire to address these different consequences of climate

[29] This fire treatment is more granular than the treatments considered in other wildfire papers, which define the wildfire at the census tract level (An et al., 2023; McConnell et al., 2021).

change. In my main specification, I define the control group as people living in blocks that never burned but within the same census tract as the fire, as shown in Figure A2(a).[30]

I define migration over time to differentiate short-term from longer-term moves and the extent of adaptation – that is, the wildfire risk of the location. For migration to be climate adaptive, the individual must both move away and to a safe location. The first component of adaptive migration is captured in whether the individual is observed in the data in a tract other than the one she lived in the year before the fire ("Moved Away from Tract"). With this definition of migration, I can capture whether people leave the burned area and the extent to which people who are displaced in the short run later return since my credit panel data allows me to track individuals over time for up to four years after the fire. I capture the second component of adaptative migration by whether the individual is observed in a low- or medium-wildfire-risk census tract after the fire ("Low or Medium Wildfire Score"). Because this measure is at the census tract level and the treatment and control groups in my main specification are census blocks within the same tract, they have the same initial wildfire risk scores.

4.3 Identification Assumptions

The DID event study relies on the assumption that the outcome trends of the treated and control groups would have been parallel in the absence of the fire. Since the exact trajectory of a wildfire is quasi-random because of exogenous factors such as wind direction, this assumption seems reasonable (Beverly and Forbes, 2023). I can evaluate its plausibility by checking whether the burned and never-burned areas were on similar trajectories before the fire and thus whether the pre-fire coefficients are statistically significantly different from zero (Roth, 2022).

Recent research suggests that since humans can cause wildfires, there is a relationship between building density and wildfire risk (Ang, 2024; Kestelman, 2024). This could pose a threat to identification if the outcome pretrends for areas with higher density are not parallel with those of lower-density areas. This is not a concern in my setting for two reasons. Although 90% of wildfires are caused by human activity (Radeloff et al., 2018), the specific path of the fire within a census tract can be considered largely caused by external, exogenous factors such as vegetation, slope, and wind direction, particularly at a spatially granular level such as the census block (B. M. Collins et al., 2007; B. Collins et al., 2009; Thompson and Spies, 2009; Estes et al., 2017; Rao et al., 2022). Thus, the exact path of the fire is random, even if there is concern about whether its starting point is random.

4.4 Robustness: Alternative Controls and Empirical Specifications

To assess the robustness of the results, I consider alternative control groups and empirical specifications. I use the never-burned blocks as the control group in my main specification to implement the

[30]For robustness, I also consider those who live in the one-mile radius (Figure A2(b)) and those who live in the one- to five-mile radius surrounding the fire (Figure A2(c)).

cleanest control group and to address the concerns from the recent DID literature about negative weighting that may arise when the eventually treated are used as the control group (Callaway and Sant'Anna, 2021; Baker et al., 2022; Roth et al., 2023). Here, I consider other control groups to assess the robustness of my results: people living in blocks within a one-mile radius of the fire and people living in blocks one to five miles away from the fire, an approach that follows the "donut" control design in the urban economics literature, which imposes some geographic distance between the treated and control units to allow for potential spatial spillovers to nearby areas (e.g., An et al. (2023) among many others).

I consider other empirical specifications in addition to my main specification, Equation 1, which I label "Baseline" or "Relative Year and Calendar Year FE." For the alternative specifications, I vary how I allow the relative trends to differ, such that they depend on the wildfire risk of the burned area or the specific fire. In all of my empirical specifications, I include individual fixed effects (μ_i), although I do not include this in the labeling of the specifications.

To allow for differential trends based on wildfire risk, I estimate Equation 3. I refer to this specification as "Interacted Wildfire Risk and Relative Year FE."

$$y_{i,f,t} = \mu_i + \sum_{r=-3,\neq -1}^{N=4} \omega_r \lambda_{r(f,t)} \times w_{z(i,f)} + \sum_{r=-3,\neq -1}^{N=4} \beta_r \lambda_{r(f,t)} \times fire_{b(i,f)} + \gamma_t + X'_{i,t}\Gamma + \epsilon_{i,f,t} \tag{3}$$

In Equation 3, the $\sum_r \omega_r \lambda_{r(f,t)} \times w_{z(i,f)}$ replaces the relative year fixed effects in Equation 1 (represented by $\sum_r \lambda_{r(i,f,t)}$). The wildfire risk score index ($w_{z(i,f)}$) is defined at the level of the census tract ($z(i,f)$) in which the individual i resides when fire f occurs.[31] This index ranges from 1 to 4, taking a value of 1 if the census tract's wildfire score is below 25, 2 if between 25 and 50, 3 if between 50 and 75, and 4 if above 75. It is interacted with the relative year indicators ($\lambda_{r(i,f,t)} = \mathbb{I}[t - E_{i,f} = r]$) to allow for differential trends depending on the wildfire risk of the burned area. The ω_r coefficients capture how much the experience of the fire impacts the individual r years relative to the time of the fire, based on the wildfire risk score of the census tract where the fire took place.

To allow for differential trends based on the specific fire, I estimate Equation 4. I refer to this specification as "Interacted Fire and Relative Year FE."

$$y_{i,f,t} = \mu_i + \sum_f \sum_{r=-3,\neq -1}^{N=4} \phi_f \lambda_{r(f,t)} + \sum_{r=-3,\neq -1}^{N=4} \beta_r \lambda_{r(f,t)} \times fire_{b(i,f)} + \gamma_t + X'_{i,t}\Gamma + \epsilon_{i,f,t} \tag{4}$$

In Equation 4, the $\sum_f \sum_r \phi_f \lambda_{r(f,t)}$ replaces the relative year fixed effects in Equation 1. This allows each fire f to have a different time trend. This empirical specification is conservative because it

[31] Recall that this variable is defined at the census tract level because this is the level at which the FEMA wildfire risk is defined.

assumes that the fire did not cause any general changes in trends for the burned areas, and it nets out this trend by allowing the local trends to differ by fire. Presumably, there could be a change in the migration trend overall in the burned areas (which is seen in Figure 3), and so not using this variation would lead to a muted estimate of the impact of the fire.

5 Migration Results

In this section, I show that people move away after their block experiences a wildfire, and though they initially move to areas with low or medium wildfire risk, they are not more likely to stay in safe areas in the longer term. This could be because of liquidity constraints: Those with high credit scores and who are more likely to receive payouts post-fire (i.e., whose homes are damaged) are also more likely to be observed in low- or medium-wildfire-risk areas in the longer run.

5.1 Preliminary Results

I compare blocks that are burned with those in the same tract that are never burned. Table 2a shows, both overall and separately for fires that do and do not receive aid, the percentage who migrate among those living in blocks that experience the first burn. Those living in blocks burned for the first time are more likely to be in a different tract in both the year after and four years after the fire, than are residents in nearby blocks in the tract that are never burned. Individuals in burned blocks are more likely to have returned by four years later, and for those living in first-burned blocks that receive aid, 21.62% of those who moved in the year of the fire return. Those who move in the year of the fire and whose location does not receive aid are not more likely to return than the individuals in the control group. Table 2b shows a similar percentage of the population moving the year after megafires and remaining away four years later for places both receiving and not receiving aid. Interestingly, for those places with megafires but without aid, the percentage of people who moved the year of the fire but come back is higher.

To understand the characteristics of the movers, I compare the summary statistics of individuals who moved to a different tract the year of the fire with individuals who did not for the population of people who lived in a census block that burned for the first time (Table B2). All characteristics are measured the year before the fire occurred. The movers and non-movers have similar average age, gender composition, likelihood of being married, and education levels. Movers are less likely to have mortgage loans. People who move also have lower credit scores, a higher number of open credit cards and open loans, and a lower credit limit and payment. These individuals would likely have more difficulty borrowing after the fire as their lower credit scores and existing engagement with financial institutions have put them in a disadvantageous position for subsequent interactions.[32]

I also investigate the characteristics of the individuals who returned for people who initially moved

[32]This is consistent with Bilal and Rossi-Hansberg (2021), who argue that those who are financially constrained may use their "location asset" and move to reduce the effect of this constraint.

in a block that burned for the first time and moved away the year of the fire (Table B3). Among the population of people who lived in a census block that burned for the first time and who moved away that year, people who returned within four years are less likely to be bankrupt and to have current delinquencies. There are no statistically significantly differences in other characteristics.

The presence of differences between the groups does not necessarily invalidate the identification strategy since the DID event study requires only that trends would have been parallel, not the same level, between the groups but for the fire. Nevertheless, the characteristics of the burned blocks are similar in levels to those of the nearby control blocks before the fire. Table 1 reports the averages of multiple demographic, migration, tract-level, and financial characteristics for the treated and control groups, the difference between the averages, and whether they are statistically significantly different.[33]

The average migration rates in the burned and never-burned areas follow parallel trends. As seen in Figure 3, before the fire, the migration rates between the two are nearly identical and thus parallel, and then those in the burned area experience a sharp increase after the fire (time 0), lending credibility to this empirical strategy. The average shares of people moving to low- or medium-wildfire-risk areas in the burned and never-burned blocks also follow parallel trends (Figure A3).[34]

There could be a concern that after the wildfire, the people in the control group are partially treated because they are in such proximity. After all, there is still an increase in the likelihood of moving away for the control group over time. This is because as time goes on, more people move away. Indeed, when I look at a 1% random sample of everyone who has ever lived in California,[35] I can see that there is similar increase in the likelihood of moving away over time between the control and the random sample (Figure A4). In actuality, the migration rate for the random sample is actually higher over time than the control group, which could be because census tracts that experience a fire tend to have populations that are older and more likely to be homeowners compared to the average in California, which are characteristics of population groups who are less likely to move (Yadav et al., 2023; Table B5).

[33] Statistically significant differences that are small in magnitude may not have a large impact on migration. For example, how much would an extra 0.23 credit cards change migration decisions? I run a regression of the likelihood of a move within the year based on the available covariates and predict the expected migration probabilities separately for the treatment and control groups. I find that the individuals living in areas that are burned are predicted to have lower migration probabilities than those in the control group (Tables B4 and B5).

[34] Since the FEMA wildfire risk score utilized in the main specification is defined at the census tract level and the treated and control groups are within the same same tract, they should theoretically have the same risk. However, because of the stacked nature of the regression, there are duplicate entries for the control group, so that is why the estimates diverge. Both the treatment and control groups experience a decrease and then increase around the time of the fire. This could be evidence of regression to the mean, as areas that are burned are of higher wildfire risk, so moving away from these areas will be more likely to be to a low- or medium-wildfire-risk area.

[35] I take the sample of everyone who moved in the year 2016 as my year 0 so that I can have a balanced sample to measure migration across the pre- and post-time periods.

5.2 Event Study Results for Migration

Figure 4 shows the results from estimating Equation 1, plotting the β_r coefficients. The coefficients are not statistically significant for years before the fire and then become positive and significant for years beginning with the one after the fire. Thus, the fire causes people to move away and stay away. The coefficients imply that, two years after the fire, individuals living in areas burned for the first time are 10.7 p.p. more likely to have moved away from the tract they lived in the year before the fire, a 47.8% increase in the likelihood of moving.[36] By the fourth year, this number remains elevated, though it is slightly smaller at 7.4 p.p. (21.0%). If we look at Figure 3, the treated group has a dip by year four in the likelihood of moving, suggesting that a group of people in the burned blocks move away and then return, consistent with Table 2. Thus, the fire causes an increased likelihood of out-migration that persists over the longer term (i.e., at the four-year horizon), even if a portion of the population returns.

This result is robust to my using a variety of different control groups and empirical specifications. Figure A5 plots the migration results for the areas first burned across the various control groups: the never burned ("Never Burned"), those within one mile of the perimeter of the fire ("One Mile Away"), and those in a one- to five-mile radius from the fire ("One to Five Miles Away"). The control group in the main specification is every census block that is never burned that is within the same census tract ("Never"). I use this as my main specification because wildfire risk is defined at the census tract level, which ensures that my treatment and control groups have the same risk. To assuage concerns that the never-burned areas are somehow different for some unmeasured reason (e.g., a deep canyon that acts as a fire break), I also consider as a control the census blocks within one mile of the fire perimeter ("One Mile Away"). Other papers have used a "donut" control group to allow for spillover effects to the immediate area (i.e. An et al., 2023), an approach that I employ as well. I include within the control group those living in census blocks one to five miles from the fire perimeter ("One to Five Miles Away"). I find similar migration results across the specifications with these control groups.

Figure A6 shows the results of the event study for the first burn across different empirical specifications. The baseline specification ("Relative Year and Calendar Year FE") controls for general year trends with the calendar year fixed effects and assumes that the treatment effects across the years are similar by having a single set of relative year fixed effects. I also consider another specification that allows for differential trends in wildfire risk by interacting each wildfire risk category with the relative year ("Interacted Wildfire Risk and Relative Year FE").[37] This is to allow for the possibility that areas where the wildfire is more surprising (i.e., those with low wildfire risk) may exhibit different trends from higher-risk areas since there could be selection in the types of people who choose to live in these different areas. The final empirical specification I consider allows each

[36] This percentage is calculated with the percentage of the control group who are in a different tract two years before the year of the fire as the denominator. All percentage changes are calculated using the migration rates of those in the control group the associated number of years before the fire.

[37] I define wildfire risk in four categories: "Low," "Medium," "High," and "Very High."

fire to have a specific trend ("Interacted Fire and Relative Year FE"). This is the most conservative specification because it takes out any change in the migration trend driven by the experience of a wildfire in the burned areas, which is arguably part of the relevant treatment effect. Across all three empirical specifications, I find that my coefficients are similar in magnitude and follow similar trajectories (i.e., an increase in the likelihood of moving away and then a dip four years after the fire), though the most conservative estimator yields smaller coefficients than the others. However, for the estimates four years after the fire, all three are of similar magnitude and show a statistically significant increase in the likelihood of being seen in a different tract. Thus, the results, especially the longer-term migration results, are similar across the various empirical specifications.

I also consider another definition of migration: whether the individual is observed in at least two different tracts within the focal year ("Moved Tract this Year"). In Figure A10, I find that wildfires cause people to be more likely to move in a given year, even four years after the fire.[38] This could be because individuals move away after the fire and then move again, which explains why they are in a safe tract after two years but not after four years. It could also capture housing instability as individuals reel from the instability of being displaced. The year of the fire, those in the burned block are 16.0 p.p. more likely to move, a 122.8% increase in the probability of moving. Four years after, individuals still have an elevated likelihood of moving (13.1 p.p. or 87.8%), suggesting the experience of a fire has longer-term migration consequences.

5.3 Event Study Results for Adaptive Migration

The results so far show that people are moving, but the risk level of the destinations need to be considered. Next, I run the same stacked DID event study regression from Equation 1 with the outcome being an indicator for whether the individual lives in a census tract with low or medium wildfire risk. Because the wildfire risk score is defined at the census tract level, the treated and control units have the same score because they are within the same tract. This outcome does not condition on migration.

Figure 5 shows the results for adaptive migration. After two years, those who are in a block burned for the first time are 5.5 p.p. more likely to be in a low or medium wildfire risk area than those in the never-burned blocks, a 23.9% increase. Four years later, this falls to 1.7 p.p. (6.2%) more likely and is no longer statistically significant.

For robustness, I again consider a variety of different empirical specifications. The same pattern of an initial increase and then decrease by year four in the likelihood of being in a low- or medium-wildfire-risk area appears across the different empirical specifications, as seen in Figure A8. None of the coefficients are statistically significant when I control for fire-specific trends in the "Interacted Fire and Relative Year FE" specification with the never burned as the control group, and for the fourth year after the fire, the coefficients are all statistically insignificant across the specifications.[39]

[38] The pre-fire likelihood of moving is similar (Figure A10).

[39] It is difficult to interpret the adaptive migration results when I use various control groups because the wildfire

5.3.1 Counterfactuals

Since burning of a block induces people to move, those in burned blocks could be mechanically more likely to be observed in low- or medium-wildfire-risk areas than those in never-burned blocks. This is because the treatment and control blocks have the same risk score as it is defined at the census tract level and tracts that burn tend to have higher wildfire risk. Thus, since those in census blocks that burned have higher migration rates, they could be more likely to appear in low- or medium-wildfire-risk areas just because they are more likely to move. One way to test this possibility is to analyze the risk of the destination conditional on moving.

Taking the population of movers across California overall, movers within areas burned for the first time before the fire, and movers in first-burn blocks after the fire, Figure A11 shows that though the likelihood of an individual's being seen after the fire in a tract with very high wildfire risk tract (i.e., FEMA wildfire risk score above 75) is lower than that of being seen in such tracts before the fire for movers in blocks that burned for the first time, it is still over three times as high as the likelihood of the average California mover. To formally compare the movers from the first-burned areas with the average Californian, I take everyone who was living in a census block that is burned for the first time and moves the year of the fire, and I randomly assign them the location of a mover in California. I run the same stacked DID event study regression from Equation 1 against the never-burned control group using the randomly assigned moves.[40]

The results (Figure A12(a)) show that the migration rates to low- or medium-wildfire-risk areas is lower than the rate for a random California mover for the two years after the fire and are similar in magnitude for the fourth year after it. Thus, individuals who experienced a wildfire for the first time are not more likely to move to a low- or medium-wildfire-risk area than is the average Californian, suggesting that there could be some selection of individuals who choose to move into these risky areas in the first place.

The population who chooses to move into these risky areas might be selected because of their preferences since they remain three times as likely to move to an area with very high wildfire risk – even after experiencing a fire (Figure A11). A more relevant counterfactual group could be the movers from the control group, who had also initially chosen to live in those areas. To assess this, I estimate Equation 1 comparing those who moved the year of the fire in the blocks that burned for the first time with movers in the never-burned blocks within the same census tract. Figure A12(b)

risk is defined at the census tract level. In my main specification, because I compare census blocks that are first burned with those never burned within the same tract, they have the same starting wildfire risk score. The control groups that are defined as individuals within one mile and those between one and five miles away from the perimeter of the first fire have pre-fire coefficients that are statistically significantly different from zero and that decrease the year of the fire. This could reflect regression to the mean in that the areas that are burned have higher wildfire risk compared to the control groups in those cases, so those that move to the burned area would be moving from a lower-wildfire-risk area. Nevertheless, the general trends of the coefficients are qualitatively similar across the control groups, in that there is an increase and then a decrease in the likelihood of being in a low- or medium-wildfire-risk tract after the fire, as can be seen in Figure A7.

[40] I randomly assign locations 100 times to obtain the standard errors for the coefficients.

shows that those who moved from the first-burn blocks are more likely to move to a low- or medium-wildfire-risk than movers from the nearby never-burned blocks. Of those who chose to live in these areas and presumably have similar preferences but one experiences a burn and the other does not, the burned movers are more likely to move to a safe area in the short run, though this effect also becomes statistically insignificant by the fourth year.

5.4 Heterogeneity Analyses

To understand the underlying mechanisms that may influence an individual's decision to adaptively migrate, I consider situations where there could be evidence of constrained vs. unconstrained migration. I analyze whether adaptive migration choices differ by whether the individual likely received a payout post-fire and whether the individual had a high credit score. These descriptive analyses suggest that liquidity constraints prevent people from moving adaptively. I also investigate whether migration choices differ over time and as a place burns repeatedly.

5.4.1 Budget Constraints and Constrained Migration

Certain factors could keep people from moving adaptively. There are two requirements for people to choose to adaptively migrate: They must want to move to safe areas, and they must be able to do so.[41] It is difficult to disentangle the desire from the ability to move when we look solely at the outcome of where people choose to move, but the evidence below suggests that liquidity constraints prevent some people from moving adaptively.

5.4.2 Damaged vs. Undamaged Homes

I compare the adaptive migration responses for those in damaged and undamaged homes to investigate the role of preferences and financial constraints. It is important to separately consider those with and without property damage as their financial decisions differ after the fire (Biswas et al., 2023).[42] One hypothesis is that an individuals' location choice solely reflects their preferences. Migration increases mechanically for those whose homes are damaged because their homes are destroyed. Those whose homes are not damaged could be interpreted as moving according to their preferences because they did not need but rather chose to move. Thus, if moving to a low- or medium-wildfire-risk area is viewed as optimal for these individuals, I would expect that people whose homes escape unscathed and move do so.

Another hypothesis takes into consideration the resources provided for those whose homes are damaged vs. those whose homes are not. The former could have increased migration and be able

[41] Refer to subsection 2.1 for a more detailed discussion.

[42] Biswas et al. (2023) find that 90-day delinquencies were 4 p.p. higher for properties damaged by wildfires and prepayments were 16 p.p. higher for properties that were damaged by wildfires, with no significant changes for undamaged properties inside the burned area. Because there are not increased sales or refinances, they hypothesize that the increased prepayments are due to insurance claims. This suggests that many affected households do not use their insurance settlements to rebuild the damaged homes.

to move adaptively because the damage to their homes unlocked financial resources – for example, an insurance payout.[43] Those with undamaged homes may also move because they are unable to afford to remain, they do not want to stay in the risky area, or infrastructure damage renders the location unlivable. Even for those who desire to move to a safe place, the next location choice could be driven by cost considerations, such as the affordability of the area. Therefore, it could be possible that both people whose homes are damaged and not damaged are more likely to move away, though only the former are more likely to move to safe areas because they received the financial resources to do so.

To test these hypotheses, I estimate Equation 1 separately for those whose homes are damaged and those whose homes are not. Although in Figure 4 I find that individuals living in census blocks that are burned are more likely to move away, these moves could be mechanically attributable to the fact that people are forcibly displaced because their homes are burned. To investigate this, I combine the CAL FIRE DINS address-level damage data with the Infutor data to separately evaluate the migration responses of people whose homes were found to have damage and those of people whose homes remained unscathed.[44] I flag individuals whose address is listed to have damage in the DINS data as "Damaged," and I define the addresses within a burned block but not flagged as "Not Damaged." I find a 10.2 p.p. increase in the likelihood of moving for those whose homes have damage, which is 84.0% higher than that for the control group (Figure A15).[45] However, I also find a 1.9 p.p. (15.6%) increase in the likelihood of moving for those whose homes are nor found to have damage, suggesting that the migration results are not driven solely by those who need to move because their homes are unlivable.[46] For the fourth year after the fire, these results grow to 16.7 p.p. (75.6%) for those with damage and 4.1 p.p. (18.6%) for those without.

I find that people whose homes are damaged are 6.1 p.p. (49.6%) more likely to go to a low- or

[43] Other potential factors could lead to those with damaged property receiving more resources. In California, Proposition 19 allows those whose homes are damaged to transfer their tax burden to a new home within the state. Additionally, after a fire, the insurance premiums in the affected area will increase as insurers update their fire risk models based on historical fire incidence. (For details about California's institutional background, see Appendix C.) Higher premiums could in turn price former residents out of the area. There are also specific government grants and loans available to individuals whose homes are damaged, though resources are also available for people whose home escaped damage.

[44] Because of data limitations and power concerns, for the damage analysis, I define the fire term to be for any fire, instead of restricting it to the first fire. I also validate that the adaptive migration results are similar across the two datasets, using the same specification and the same time period (i.e., people experiencing first burns between 2014 and 2021), and find similar results (Figure A13; Figure A14).

[45] The migration rates in the Infutor dataset are lower than in the UCCCP data (Figure A13). This could be because of issues with linkage over individuals across time since Infutor, whose product is generally used for advertising, has an incentive to have the correct address for a given individual at a moment in time but not necessarily to connect the same individual over time. The "Damaged" indicator includes all levels of damage, ranging from minimal to destroyed, which could also explain why not all individuals are seen to move if their home is damaged.

[46] It could be that people whose homes are not directly damaged are unable to live in the area because of infrastructure damage. Nevertheless, this would not change but rather strengthen my interpretation of the importance of financial constraints. Though people with undamaged homes must pay the migration cost by being forcibly displaced, they do not receive the additional resources associated with having damaged property. This suggests that the difference in post-fire resources, which loosens liquidity constraints, can explain the lack of adaptive migration for the group with no damage.

medium-wildfire-risk score tract after two years and are 11.9 p.p. (64.8%) more likely to do so after four years. However, those whose homes are not damaged are not more likely to be seen in a safe area, anytime after the fire (Figure A16). This is consistent with the second hypothesis about financial resources helping individuals move to safe areas.

For robustness, I consider other definitions of people whose homes are not damaged and find similar results. My main definition for a home that is not damaged are one that is in a burned block but does not belong to the group of homes found to be damaged ("Within Burned Block, Not Confirmed Damage"). Next, I consider the homes evaluated by CAL FIRE and definitively marked as having no damage ("Confirmed Not Damaged"). I also define an indicator for homes not confirmed to have damage ("Not Confirmed Damage"). The results in Figure A18 show an increase in the likelihood of moving away across all of these definitions of undamaged homes, though the statistical significance of the "Confirmed Not Damaged" estimate differs because of power issues. Similarly, in Figure A18, there is no statistically significant effect on the likelihood of moving away across all of these definitions of undamaged homes.[47]

5.4.3 High vs. Low Credit Score

Individuals might turn to financial institutions to help weather the impact of the fire. Having access to loans and credit cards can help people who experienced a fire borrow to have higher liquidity in the present to make optimal decisions. Those with higher credit scores can engage with financial institutions on more advantageous terms. Thus, I view the credit score as a proxy of an individual's ability to access financial resources needed after a large shock, such as a fire.[48]

I interpret people with higher credit scores as being less financially constrained and their migration choices to thus better reflect their preferences. Differences in migration decisions between groups with high and low credit scores could be evidence that the latter are constrained, assuming that the two groups have similar preferences.[49]

I estimate Equation 1 separately by credit score. I define people with high credit scores as those

[47]There is a larger increase in the magnitude of the coefficients on "Confirmed Not Damaged" for the migration and adaptation results, but this could be because homeowners who requested the damage inspection could have done so for insurance purposes and already wanted to move. Moreover, the results are not statistically significant and have large confidence intervals because there are few observations of inspected properties confirmed to not have any damage.

[48]Credit scores may also be a proxy for individuals' income, although the literature is divided on this question. For instance, Albanesi et al. (2017) find that credit score and income are strongly positively correlated, whereas Beer et al. (2018) find only a moderate correlation. For the purposes of my interpretation, this relationship is not key as I am interested in the extent to which people move and whether access to financial institutions alters migration choices.

[49]It could also be that those with higher credit scores are more firmly tied to a place given their likely greater home equity. A fire either could free them from their current location, such that they could be more likely to move, or could make them reluctant to relocate. The results from Biswas et al. (2023) suggest that individuals are less likely to rebuild their homes, suggesting that they are more likely to move away. I also find similar results when I run the analysis by homeownership status.

with scores of 700 or higher and those with low credit scores as having scores lower than 700.[50] I compare individuals in the same credit score category and in blocks burned for the first time with those in never-burned blocks within the same census tract. As seen in Figure A19, I find that individuals across the credit distribution are more likely to move, though those with high credit are statistically significantly more likely to remain away after four years. Similarly in Figure A20, the high credit scores are statistically significantly more likely to move to a low- or medium-wildfire-risk area after four years. These results suggest that people with high credit are more likely to move away and to safe areas than people with low scores, which could be interpreted as the latter being constrained in their migration choices.

5.4.4 Investigating Other Mechanisms

The previous results suggest that financial constraints could hinder adaptive migration. This is because people whose homes are damaged and people with high credit scores are less likely to be liquidity constrained and are more likely to move to safe areas. To consider additional mechanisms and potential explanations, I estimate Equation 1 across other dimensions of heterogeneiety, and the results reinforce the importance of liquidity constraints in preventing adaptive migration.

One potential explanation is that more educated people are more likely to move adaptively because they can better update or incorporate additional information into their migration decision. More educated people are also more likely to have high credit scores (LendEDU, 2017). To test this channel, I estimate Equation 1 separately for the group with a college degree and that without using the UCCCP data, which include education status.[51] I find that both education groups in the first-burned blocks are more likely to move away than their counterparts in never-burned blocks (Figure A21). However, people without a college degree are more likely to move adaptively, which runs counter to the hypothesis that education is driving the adaptive migration effect (Figure A22).[52]

Another potential correlate of credit scoress is age. People of working age, which I define as younger than 55, could be more likely to move for reasons beyond wildfire risk, such as work or school continuity for their children. I choose 55 as the age cut-off because Proposition 19 allows those who are above 55 and those whose homes are destroyed by a wildfire to transfer their tax burden to another property in California (BOE, 2021). Older people (i.e., over 55) may also be retired and could have chosen to live in the risky places to begin with because of their preferences, and they could be more likely to move to a location with similar environmental amenities. I find that both groups are more likely to move away from the burned area (Figure A23), though neither is more likely to be in a safe area in the longer term than their counterparts in never-burned areas (Figure A24). This suggests that the adaptive migration results are not driven by age.

[50] This is similar to the average credit score in my treated group (701) and the average credit score in California, which was 712 as of March 2024 (Equifax, 2024).

[51] In my main specifications, I include whether an individual has a college degree as a control.

[52] This information channel would offer a less satisfactory account of the results of the damage analysis.

I also consider heterogeneity by homeownership status. Typically, homeowners purchase their homes with a mortgage, which would require some sort of wildfire insurance. Those who are owners, and thus more likely to receive a payout after the wildfire, are more likely to move to safe areas in the longer term, providing further evidence that financial constraints are an important barrier to adaptive migration (Figure A25; Figure A26).

Taken together, these heterogeneity analyses are consistent with financial constraints being a barrier to adaptive migration. These results show that those who are less financially constrained – either by having easier access to financial institutions or who are more likely to receive a payment after the wildfire – are more likely to move to safe areas.

5.4.5 Effects Across Time Periods and Subsequent Fires

Given the increase in wildfires in California and climate change discussions over the past decade, there could have been a change in people's beliefs about the likelihood of future fires, subsequently impacting their migration decision. More recent fires could be expected to be associated with more migration as people become more aware of the increased likelihood of subsequent fires. It could also be that with increased awareness about climate risk, people who choose to live in areas with higher wildfire risk have a strong preference for the associated environmental amenities and thus are less likely to move.

To test this conjecture, I use the Infutor data, which cover a longer period of data than the UCCCP data, and I employ the same empirical strategy across different sample time periods.[53] In particular, I look at the migration rates and wildfire risk score for 2000-2019 and then separately for 2000-2010 and 2010-2019 and plot them on the same graph.[54] I find similar migration rates across periods, consistent with the finding in the political science literature that Americans' attitudes towards climate change have not substantially changed over the past two decades (Egan and Mullin, 2017).[55]

I also assess whether there are different migration choices among people in an area that burns repeatedly. To do so, I estimate Equation 1 but, instead of comparing people in blocks that burn for the first time with those in blocks never burned, I compare people in blocks that burn for the second time with people in the never-burned blocks, people in twice-burned blocks with people in first-burned blocks, and people in thrice-burned blocks with people in first-burned blocks, where the control is within the same tract.[56] I find no difference in migration among people in the twice-

[53] As an additional validation exercise between the two datasets, I estimate Equation 1 using the Infutor and UCCCP datasets across the same time period: 2014-2021. Although the migration rate from the Infutor data is lower than that from UCCCP, they follow qualitatively similar patterns. The migration results can be seen in Figure A13 and the adaptation results in Figure A14.

[54] I omit 2020 to abstract from the COVID-19-related migration changes.

[55] The finding that people who experienced a wildfire between 2000 and 2010 are statistically significantly more likely to migrate also serves as evidence of the role of liquidity constraints since, before the 2008 financial crisis, all individuals were able to easily obtain a loan, even those with low credit scores. Thus, it could have been that they could more easily finance living in a safe area.

[56] I count the number of fires starting from 1950, the year in the CAL FIRE data where there begins to have more populated entries.

burned and never-burned blocks. Indeed, I see a statistically significant negative effect on migration among people in a twice-burned block in comparison to people in a first-burned block, meaning that areas that have previously burned see less out-migration. There is also a statistically insignificant negative migration effect for people in blocks that experience the third vs. second fire. This could reflect that people respond differently to repeated burns. It could also mean that people living in areas that have previously burned are selected in the sense that they may be more tolerant of fires (Zabek, 2024).

6 Impact of Government Aid

Government aid could hinder or facilitate adaptive migration. On the one hand, Federal Emergency Management Agency (FEMA) provides aid for individuals to rebuild or repair their homes, encouraging residents to return to the burned block. On the other, there is aid to cover short-term rent, which can be used anywhere in the country, facilitating migration.[57] I thus investigate the direction of the effect of aid on adaptive migration empirically.

6.1 Preliminary Results: Government Aid vs. No Government Aid

To assess the impact of receipt of government aid on migration, I amend Equation 1 to include an additional interaction term ($\sum \alpha_r \lambda_{r(f,t)} \times fire_{b(i,f)} \times aid_{c(i,t)}$) that captures the effect of aid receipt ($aid_{c(i,t)}$) and is equal to one if the individual i lives in a county c authorized to receive Individual and Households Program (IHP) aid in year t.

The new estimation equation is:

$$\begin{aligned} y_{i,f,t} = \mu_i + \sum_{r=-3,\neq -1}^{N=4} \lambda_{r(f,t)} + \sum_{r=-3,\neq -1}^{N=4} \alpha_r \lambda_{r(f,t)} \times fire_{b(i,f)} \times aid_{c(i,t)} \\ + \sum_{r=-3,\neq -1}^{N=4} \beta_r \lambda_{r(f,t)} \times fire_{b(i,f)} + \gamma_t + X_{i,t}^{'}\Gamma + \epsilon_{i,f,t} \end{aligned} \tag{5}$$

Since receipt of government aid is not as-good-as-random and can be related to factors that also impact migration, this specification does not yield a causal estimate of the effect of aid. Nonetheless, the correlations shed light on the relationship between aid and individual outcomes. In Figure 6, I find that individuals in blocks that are burned for the first time and that receive aid are 16.3 p.p. (72.8%) more likely to have moved away two years after the fire whereas those in blocks that are burned but do not receive aid are 2.2 p.p. (9.8%) more likely to have moved. After four years, those in burned blocks that receive aid are 9.5 p.p. (27.0%) more likely to remain away, and those in blocks that did not receive aid are 3.9 p.p. (11.0%) more likely. The coefficients for the fires

[57] Details about government aid can be found in subsection 2.3.

with aid and those without aid are statistically significantly different from each other for the four post-fire years at the 5% level.

Government aid is also associated with more adaptive migration. Figure 7 shows that individuals in blocks that are burned for the first time that receive aid are 6.8 p.p. (27.3%) more likely to move to a low- or medium-wildfire-risk tract after two years, and those in burned blocks that did not receive aid are 3.4 p.p. (13.5%) more likely, though the coefficients are not statistically significantly different at the 5% level. After four years, people in burned blocks that receive aid are 5.3 p.p. (18.3%) more likely to be in safe areas, and those in burned blocks that do not receive aid are 2.2 p.p. (7.5%) less likely; these coefficients are statistically significantly different at the 5% level. However, conducting the same placebo counterfactual analysis as I did in subsubsection 5.3.1, I find that people are less likely to move to low- or medium-wildfire-risk areas after two years than if they were a random mover within the sample, though they are more likely after four years (Figure A29).

Receipt of aid is hypothesized to help those with low credit scores. I find that individuals across the credit groups who are in a block hit by a first fire that receives aid are more likely to move away (Figure A28), though even with aid, only the individuals with high credit scores are statistically significantly more likely to be in a low- or medium-wildfire-risk area (Figure A29). People with high credit scores are more likely to move (Figure A30) and to do so to a safe place (Figure A31), even without aid, though the coefficients are not statistically significant for the fourth year for people in areas with fires but not aid. For people with low credit scores, receiving aid is associated with an increased likelihood of moving (Figure A32) and of doing so to a safe place (Figure A33), though the coefficients are not statistically significant for the fourth year. However, in the case of fires without aid, people with low credit scores are less likely to be in a safe place after four years, though the coefficient is not statistically significant. Since the short-term rental aid can be provided for up to 18 months (FEMA, 2024b), the dissipation of the effects after two years could reflect the impact of no longer receiving aid.

In conclusion, government aid is associated with increased migration and migration to safe areas. People with low credit scores do not move to safe areas, even with aid. These results could be interpreted as more severely affected areas having larger migration responses and being more likely to receive aid or as aid helping individuals move away and move to safer areas.

6.2 Causal Impact of Aid

6.2.1 Instrument: Political Competitiveness

Factors correlated with aid receipt could also impact migration, which would bias my estimates such that the coefficients from Equation 5 fail to reflect the causal impact of aid. For example, fires for which aid is extended might be more destructive, which would also cause more people to move. This would lead to overestimation of the impact of the aid on migration. Alternatively, areas that receive aid may have disproportionate shares of groups who have lower migration rates, such as homeowners. This would lead to an underestimation of the impact.

To assess the causal effect of aid, I utilize a novel instrument that takes advantage of the fact that electoral considerations affect aid provision. I find that wildfires in counties that are politically competitive are more likely to receive FEMA IHP aid.[58] I define political competitiveness as the difference in the voter share between the highest and second highest candidates in the most recent presidential election, which I obtain from the MIT Election Labs.[59] I find that counties that are within 5% are statistically significantly much more likely to receive aid, including when conditioning on experiencing a fire or a megafire (Table 4). Among counties that experience a fire, the politically competitive ones are almost three times more likely to receive aid (0.14 vs. 0.05). Counties that experience a megafire are four times more likely to draw aid (0.28 vs. 0.07).

Politically competitive and noncompetitive counties are similar on a variety of characteristics, giving credibility to the idea that electoral incentives are what lead to greater aid. Although politically competitive counties are more likely to experience any fire, conditional on counties' experiencing a fire, they still are three times more likely to receive aid. Competitive and noncompetitive counties are indistinguishable in the size of the fires, number of fires and megafires, and likelihood of experiencing a megafire (Table 4). Conditional on the counties' receiving aid, there is no statistically significant difference in the amount of aid received. This makes sense, as the scope for the president's discretion is limited to whether the disaster is declared, not the specific amounts given out, which are determined following FEMA protocol and are less manipulable.

Since California has voted reliably Democrat in every election since 2000, the start of the considered period, it may seem surprising that the president would have electoral incentives to extend aid to politically close counties. However, the political science and economic history literatures have highlighted the political benefits from aid and politicians taking advantage of this phenomenon in swing areas (Wright, 1974; Fleck, 2001; Fishback et al., 2007; Reeves, 2011; Husted and Nickerson, 2014; Boustan et al., 2017; Jou and Morgan, 2024). Congressional districts within California are sometimes competitive, and boosts to representation in the House of Representatives results in additional political power. Vote shares in presidential elections may proxy the political closeness of a county overall or the congressional districts within it, which is relevant for local elections. Because the benefits of aid receipt for incumbent politicians are well documented (Reeves, 2011; Clemens et al., 2024; among others), goodwill may transfer to the party in congressional elections. This seems plausible because straight-ticket voting, the practice of voting for down-ballot candidates of the same political party as the president, is common in the United States, with the Pew Research

[58]This result is consistent with previous papers that connect post-disaster policies with political motives. For instance, Henkel et al. (2022) find that hurricanes in an election year (i.e., an even-numbered year) are more likely to trigger larger amounts of government transfers and that the affected areas experience larger population growth as a result. Although I try their instrument, I do not find evidence that temporal proximity to an election year predicts receipt of government aid for the California wildfires.

[59]For years with presidential elections, political competitiveness is defined by vote shares in the election that year. For years without presidential elections, political competitiveness is defined by the vote shares in the most recent presidential election. My specification is robust to my using the previous years' presidential election results.

Center finding that in the 2020 election, only 4% of registered voters said that they planned to vote for Biden and the Republican candidate for House in their district or Donald Trump and the Democratic House candidate (Atske, 2020).[60] Thus, though California overall may not be politically competitive, the president may still have an incentive to provide aid to help the other members of his or her party to increase overall political representation.

6.2.2 Empirical Strategy: DID and DID IV

For ease of interpretation for the instrumental variable (IV) analysis, I use a difference-in-differences (DID) specification to evaluate the impact of receipt of any FEMA IHP aid by condensing the main event study specification:

$$\begin{aligned} y_{i,f,t} = \mu_i + post_{f,t} + \alpha post_{f,t} \times fire_{b(i,f)} \times aid_{c(i,t)} \\ + \beta post_{f,t} \times fire_{b(i,f)} + \gamma_t + X'_{i,t}\Gamma + \epsilon_{i,f,t} \end{aligned} \tag{6}$$

In Equation 6, I add another interaction term of an indicator for county receipt of aid at time t, $post_{f,t} \times fire_{b(i,f)} \times aid_{c(i,t)}$, to Equation 1. The coefficient of interest α captures the average impact of wildfire aid receipt at any point after the treatment. I call this specification the "DID regression."

To obtain the causal effect of IHP aid, I instrument for the aid indicator by whether the individual is living in a politically competitive county at the time of the fire. The first stage of the specification is:

$$\begin{aligned} post_{f,t} \times fire_{b(i,f)} \times aid_{c(i,t)} = \mu_i + post_{f,t} + \alpha post_{f,t} \times fire_{b(i,f)} \times flip_{c(i,t)} \\ + \beta post_{f,t} \times fire_{b(i,f)} + \gamma_t + X'_{i,t}\Gamma + \epsilon_{i,f,t} \end{aligned} \tag{7}$$

The instrument, $post_{f,t} \times fire_{b(i,f)} \times flip_{c(i,t)}$, is defined at the county level and is equal to one if the year is after the year of the fire, the individual was in a block burned by the fire, and the difference in the top two vote shares in the last presidential election was within 5%. I then use the estimated $post_{f,t} \times fire_{b(i,f)} \times flip_{c(i,t)}$ term in Equation 6 to obtain the causal impact of aid on adaptive migration.

For political competitiveness to be a valid instrument for government aid, it must satisfy the relevance condition and the exclusion restriction. The relevance condition requires that a county's political competitiveness be predictive of its likelihood of receiving aid. The first stage of my two-stage least squares regression (Table 5) shows that a politically competitive county is more likely to receive FEMA IHP aid, and the F-statistic is substantially greater than 10. This result is robust to using different measures of political competitiveness, where the likelihood of aid receipt mono-

[60] Some 78% of voters said that they would vote for either Biden and the Democratic House candidate or Trump and the Republican candidate in their congressional district. The remaining 16% were split in a different way or not sure/refused to answer. This voting breakdown is similar to that for the 2016 election (Atske, 2020).

tonically decreases and loses statistical significance as political competitiveness decreases, lending additional credibility about the instrument's relevance (Table B6).[61]

The exclusion restriction requires that a county's political competitiveness impact migration outcomes through only aid receipt, nothing else. Although this condition is not directly testable, I evaluate the likelihood of receipt of other forms of government aid not related to wildfires by political competitiveness.[62] To do so, I run the following regression specification:

$$y_{c,t} = \alpha + \beta fire_{c,t} + \gamma comp_{c,t} + \zeta fire_{c,t} \times comp_{c,t} + \epsilon_{c,t} \tag{8}$$

The outcome variable ($y_{c,t}$) is defined for county c at calendar year t. The fire variable ($fire_{c,t}$) is an indicator variable equal to one if county c experienced a fire in year t. The political competitiveness variable ($comp_{c,t}$) is equal to one if the difference in the top two vote shares in the last presidential election was within 5% for county c. The interaction between the fire and political competitiveness terms ($fire_{c,t} \times comp_{c,t}$) captures whether there are differences in the outcome for politically competitive counties that experience a fire. I cluster standard errors at the year level since the budget is determined annually.

Gathering a variety of county-level data on local expenditures, non-FEMA government aid, and tax amounts, I find that though there is often increased spending after a fire, the spending increase for politically competitive counties is minimal (Table 6).[63] For politically competitive counties that experience a fire, I do find increased fire-related spending, consistent with increased aid receipt after the fire and exactly what my instrument is intended to capture.

There could be another concern that individuals in politically competitive counties may be different in ways that impact their likelihood of moving adaptively. One such difference could be their climate attitudes as those who do not believe in climate change may be not want be inclined to move in an adaptive fashion. In order to test this, I estimate the equation Equation 8 with outcomes from a climate survey as the outcome. The survey data comes from the Yale Program on Climate Change Communication, which conducts a national survey about beliefs, perceptions, and preferences regarding climate change and global warming. The regression coefficients on the interacted Fire × 5% term shows that individuals in politically competitive counties that burn are more likely to believe that global warming is happening and to support requiring utility companies

[61] In cases where the gap in political competitiveness is 10% or 15%, the margin might seem too large to be considered a close election, so the instrument no longer statistically significantly predicts aid receipt.

[62] This is a negative control test in the nomenclature of Danieli et al. (2023).

[63] Even if the amount of government aid does differ by political competitiveness, the instrument would still be relevant for government aid, defined more broadly than the FEMA program. It would be an instrument for the bundle of provided aid. However, I do not find evidence that a politically competitive county that experiences a fire receives increased aid of other types. The public assistance expenditure and the reinstated Medi-Cal are both close to statistically significance at the 10% level for the interacted Fire × 5% term. However, they are both negative, meaning that politically competitive areas that experience a fire receive less of these programs, in contrast to what would be predicted for this instrument.

to utilize renewable sources (Table B7).

6.2.3 IV Results

When estimating the DID regression (Equation 6), I find FEMA IHP aid receipt leads to a 17.0 p.p. increase (statistically significant at 1%) in the likelihood of moving away from the tract and a 5.5 p.p. increase in the likelihood of an individual's being in a low- or medium-wildfire-risk area (statistically significant at 5%, Table 7). However, when I use the instrument, I find that this measure of aid is associated with a 33.0 p.p. increase in the probability of moving away (statistically significant at 1%), suggesting that aid receipt helps individuals relocate. This estimate is almost twice the size of the DID result. Moreover, this measure of aid is associated with a statistically insignificant -2.6 change in the likelihood of an individual's being in a low- or medium-wildfire-risk-area. This result is robust to including the county-level data on local expenditures, non-FEMA government aid, and tax amounts that were used to evaluate the exclusion restriction into the regression (Table B8).[64] Although government aid does help individuals move, it does not lead them to migrate to safe areas.

These results are consistent with the fact that there are no restrictions on where the individual can move to receive aid (Table 7). This result could also be related to the results in subsubsection 5.4.2, in that the aid helps those whose homes are not damaged move away – thus leading to larger migration rates – but these groups are not more likely to move to safe areas.

7 Discussion

This project provides novel empirical estimates of the extent of adaptive migration – the movement from risky to safe areas – and documents that it is minimal in the longer term. Using geographically granular and detailed individual-level data and a stacked DID event study empirical strategy, I can precisely identify who is impacted by a wildfire and catagorize their location decision to causally identify the impact of a fire on adaptive migration, which has previously not been estimated in the literature. Overall, although people are more likely to move after a wildfire, they are not more likely to move to a safe area in the longer term.

Although my estimates for adaptive migration in the longer term are low, understanding why this is the case has important welfare implications. For adaptive migration to occur, people need to be able to assume the moving costs and to both want to and be able to migrate to safe areas. Identifying the factors which prevent adaptive migration has important consequences for policy design. I provide suggestive evidence that financial constraints may be a factor that restricts adaptive migration. People with high credit scores and people who are more likely to receive payouts immediately after the fire (i.e., those whose homes are damaged) are statistically significantly more likely to have moved to low- or medium-wildfire-risk areas after four years. These financial constraints can be

[64] I exclude the Medi-Cal data as a county-level control in this regression because there is only one year overlap in time with the other datasets.

further distinguished into liquidity constraints – which could prevent people from moving because they cannot afford the initial moving costs – and solvency constraints – which could prevent people from moving because they cannot afford to live in the safe areas. Those with high credit scores could be less likely to be bound by the solvency constraint so they can live in safer areas in the longer term. Those who received the insurance payments are less likely to be liquidity constrained, and they could also be less likely to be solvency constrained depending on the payment amount and how they use it (i.e., investing it to increase savings vs. spending it immediately as consumption).

To assess whether existing government aid can address such financial constraints, I conduct a novel causal analysis of government aid, using the fact that politically competitive counties are more likely to receive any FEMA Individual and Households Program (IHP) funding as an instrument for aid. I interpret the results from section 6 through the lens of my conceptual framework. If the barrier to adaptive migration is only the initial migration cost – a liquidity constraint – I would expect that people who receive this short-term disaster aid would have higher migration rates out of the burned area and to safe areas. If the issue is instead an inability to pay long-term rental costs – a solvency constraint – I would expect that the government aid would assist people in moving adaptively, for as long as the disaster aid allows them to afford to (i.e., until the government aid runs out). My instrumental variables analysis finds that aid leads to increased migration, though not to safe places. This suggests that the government aid helps some individuals assume the initial migration cost and that a liquidity constraint prevents some people from moving away. Since people initially move to safe areas but do not stay in the longer term, this suggests that there could be a solvency constraint that the government is not adequately addressing. These results suggest that the current aid system does not provide enough financial resources to promote long-term adaptive migration. Indeed, that FEMA's IHP aid program provides short-term rental assistance for up to 18 months after the disaster could explain why there is an initial increase in adaptive migration that dissipates after two years, as people become unable to afford to live in the safe areas.[65] Although the structure of our current aid system succeeds in helping some undertake the initial migration cost, it is not conducive for long-term adaptive migration. If the government wants to promote this adaptation strategy, it needs to change the way that aid is distributed.

One way for the government to facilitate adaptive migration is to incorporate location-specific conditions to aid. Instead of providing aid to rebuild homes damaged by natural disasters, the government could instead restrict reconstruction in risky areas, which is what Canada has done in very high flood hazard zones (Flavelle, 2019). This would not only discourage the initial residents from returning, but it would also restrict the number of people moving in. Managed retreat is another potential adaptive migration policy that moves entire communities away from areas vulnerable to climate change, such as the relocation of Isle de Jean Charles away from coastal Louisiana (Community Development, 2021). This policy is intended to maintain the community – one of the

[65] An alternative interpretation could be that individuals "forget" about the wildfire risk and change their beliefs about wildfire risk over time. This seems highly unlikely given the destructive and traumatic nature of surviving a wildfire.

amenities of the neighborhood – and to create a planned community in a safe area for the residents. However, managed retreat is expensive and requires significant coordination: In 2016, Louisiana was awarded $48 million from the US Department of Housing and Urban Development to relocate the residents of Isle de Jean Charles, though the plan took years to implement and frustrated the local community (Wendland, 2019). However, it would guarantee that the residents move to a safe area. The government could also provide aid conditional on the safety of the location. I find that individuals are already moving adaptively in the short term, suggesting that individuals have a preference for safe areas. However, people seem to return to riskier areas in the longer term, suggesting they might not be able to afford to stay in the safer locations. Providing job search assistance or longer-term rental assistance could help people stay in these safe areas. Although these policies can seem expensive, they could be cost-effective if they prevent losses from future disasters. Evaluating the cost-effectiveness of these different types of government programs would be helpful to determine the most efficient way to promote adaptive migration.

There could be other explanations for why there is too little adaptive migration. People could lack information about the risks of wildfires or about safe areas, which could prevent them from moving adaptively. Although I see some suggestive evidence that people do have some sense of the wildfire safety of an area because I find an increase in the short-term likelihood of moving to safe areas, more detailed survey data about people's beliefs would be helpful for understanding what information they have about wildfire risk. Another explanation could be that the wildfire does not necessarily impact the individual's labor market. Autor et al. (2014), Yagan (2019), among others, find a limited migration response to a labor market shock. In the case of a wildfire, one might expect even lower migration responses since the impacted individuals are still tied to their jobs in the area. I define migration at a much finer level than the commuting zone, so my results can be consistent with their findings: People may move but not move far because they retain their old jobs. Further work on the impact of wildfires on local employment and whether there are differential migration responses based on this dimension would be illuminating. This paper explores financial constraints as one potential mechanism, and assessing the others is key for future research.

When evaluating overall welfare, it is also important to consider the implications for residents of the safe areas into which people move. People in the receiving areas will experience higher congestion, increased housing demand, and increased labor supply, which may translate to increased housing prices (Schubert, 2024) and lower wages if housing supply and labor demand do not change. The government should consider changes within the receiving areas as part of policies that promote adaptive migration to minimize the negative welfare impacts on the safe areas.

In conclusion, although there is evidence that individuals who experience a fire are more likely to move away, they are not more likely to move to a safe place. Financial constraints seem to be one reason why people do not move adaptively. Government aid, as it is currently structured, does not sufficiently address this barrier to adaptive migration. Understanding the other factors preventing people from moving to safe areas is crucial for designing effective policies, especially if the government seriously considers adaptive migration a key disaster adaptation mechanism.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge (2023). "When Should You Adjust Standard Errors for Clustering?" In: *The Quarterly Journal of Economics* 138.1, pp. 1–35. ISSN: 0033-5533. DOI: 10.1093/qje/qjac038. URL: https://doi.org/10.1093/qje/qjac038 (visited on 09/12/2024).

Albanesi, Stefania, Giacomo De Giorgi, and Jaromir Nosal (2017). *Credit Growth and the Financial Crisis: A New Narrative*. DOI: 10.3386/w23740. National Bureau of Economic Research: 23740. URL: https://www.nber.org/papers/w23740 (visited on 09/21/2024). Pre-published.

An, Xudong, Stuart A. Gabriel, and Nitzan Tzur-Ilan (2023). "The Effects of Extreme Wildfire and Smoke Events on Household Financial Outcomes". In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.4353113. URL: https://www.ssrn.com/abstract=4353113 (visited on 08/28/2023).

Anderson, Sarah E., Andrew J. Plantinga, and Matthew Wibbenmeyer (2023). "Inequality in Agency Response: Evidence from Salient Wildfire Events". In: *The Journal of Politics*. DOI: 10.1086/722044. URL: https://www.journals.uchicago.edu/doi/10.1086/722044 (visited on 10/28/2024).

Ang, Qi Qi Amanda (2024). *Paradise Lost: Population Growth and Wildfire Mitigation*. Working Paper. URL: https://www.dropbox.com/scl/fi/ozoije9tr19epp73djoo0/aang_jmp_240126.pdf?dl=0&rlkey=hff4h8fupwewql0x6puswuzc1&st=h2l0ay3x (visited on 09/16/2024).

Annan, Francis and Wolfram Schlenker (2015). "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat". In: *American Economic Review* 105.5, pp. 262–266. ISSN: 0002-8282. DOI: 10.1257/aer.p20151031. URL: https://www.aeaweb.org/articles?id=10.1257/aer.p20151031 (visited on 04/29/2025).

Atske, Sara (2020). *Large Shares of Voters Plan To Vote a Straight Party Ticket for President, Senate and House*. Pew Research Center. URL: https://www.pewresearch.org/politics/2020/10/21/large-shares-of-voters-plan-to-vote-a-straight-party-ticket-for-president-senate-and-house/ (visited on 09/22/2024).

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song (2014). "Trade Adjustment: Worker-Level Evidence *". In: *The Quarterly Journal of Economics* 129.4, pp. 1799–1860. ISSN: 0033-5533. DOI: 10.1093/qje/qju026. URL: https://doi.org/10.1093/qje/qju026 (visited on 09/23/2024).

Baker, Andrew C, David F Larcker, and Charles C Y Wang (2022). "How Much Should We Trust Staggered Difference-In-Differences Estimates?" In: *Journal of Financial Economics* 144.2, pp. 370–395.

Baylis, Patrick W. and Judson Boomhower (2021). *Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of U.S. Wildfires*. DOI: 10.3386/w29621. National Bureau of Economic Research: 29621. URL: https://www.nber.org/papers/w29621 (visited on 07/21/2022). Pre-published.

Beer, Rachael, Felicia Ionescu, and Geng Li (2018). “Are Income and Credit Scores Highly Correlated?” In: URL: https://www.federalreserve.gov/econres/notes/feds-notes/are-income-and-credit-scores-highly-correlated-20180813.html (visited on 09/21/2024).

Behrer, A. Patrick and Valentin Bolotnyy (2023). *Moving to Adaptation? Understanding the Migratory Response to Hurricanes in the United States*. Policy Research Working Papers. The World Bank. DOI: 10.1596/1813-9450-10528. HDL: 10986/40119. URL: https://hdl.handle.net/10986/40119 (visited on 11/06/2024).

Belasen, Ariel R. and Solomon W. Polachek (2009). “How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida”. In: *Journal of Human Resources* 44.1, pp. 251–276. ISSN: 0022-166X, 1548-8004. DOI: 10.3368/jhr.44.1.251. URL: https://jhr.uwpress.org/content/44/1/251 (visited on 10/09/2025).

Benevolenza, Mia A. and LeaAnne DeRigne (2019). “The Impact of Climate Change and Natural Disasters on Vulnerable Populations: A Systematic Review of Literature”. In: *Journal of Human Behavior in the Social Environment* 29.2, pp. 266–281. ISSN: 1091-1359. DOI: 10.1080/10911359.2018.1527739. URL: https://doi.org/10.1080/10911359.2018.1527739 (visited on 08/15/2024).

Bento, Antonio M., Noah Miller, Mehreen Mookerjee, and Edson Severnini (2023a). “A Unifying Approach to Measuring Climate Change Impacts and Adaptation”. In: *Journal of Environmental Economics and Management* 121, p. 102843. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2023.102843. URL: https://www.sciencedirect.com/science/article/pii/S009506962300061X (visited on 04/29/2025).

– (2023b). “Incidental Adaptation: The Role of Non-climate Regulations”. In: *Environmental and Resource Economics* 86.3, pp. 305–343. ISSN: 1573-1502. DOI: 10.1007/s10640-023-00793-3. URL: https://doi.org/10.1007/s10640-023-00793-3 (visited on 04/29/2025).

Berlemann, Michael and Max Friedrich Steinhardt (2017). “Climate Change, Natural Disasters, and Migration—a Survey of the Empirical Evidence”. In: *CESifo Economic Studies* 63.4, pp. 353–385. ISSN: 1610-241X. DOI: 10.1093/cesifo/ifx019. URL: https://doi.org/10.1093/cesifo/ifx019 (visited on 08/15/2024).

Beverly, Jennifer L. and Air M. Forbes (2023). “Assessing Directional Vulnerability to Wildfire”. In: *Natural Hazards* 117.1, pp. 831–849. ISSN: 1573-0840. DOI: 10.1007/s11069-023-05885-3. URL: https://doi.org/10.1007/s11069-023-05885-3 (visited on 07/31/2024).

Bilal, Adrien and Esteban Rossi-Hansberg (2021). “Location as an Asset”. In: *Econometrica* 89.5, pp. 2459–2495. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA16699 (visited on 08/31/2023).

– (2023). *Anticipating Climate Change Across the United States*. DOI: 10.3386/w31323. National Bureau of Economic Research: 31323. URL: https://www.nber.org/papers/w31323 (visited on 06/13/2023). Pre-published.

Billings, Stephen B., Emily A. Gallagher, and Lowell Ricketts (2022). “Let the Rich Be Flooded: The Distribution of Financial Aid and Distress after Hurricane Harvey”. In: *Journal of Finan-*

cial Economics 146.2, pp. 797–819. ISSN: 0304405X. DOI: 10.1016/j.jfineco.2021.11.006. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304405X21005067 (visited on 02/13/2024).

Biswas, Siddhartha, Mallick Hossain, and David Zink (2023). *California Wildfires, Property Damage, and Mortgage Repayment*. Working paper (Federal Reserve Bank of Philadelphia) 23–05. Federal Reserve Bank of Philadelphia, pp. 23–05. DOI: 10.21799/frbp.wp.2023.05. URL: https://www.philadelphiafed.org/-/media/frbp/assets/working-papers/2023/wp23-05.pdf (visited on 08/29/2023).

Bittle, Jake (2023). *The Great Displacement: Climate Change and the Next American Migration*. ISBN: 978-1-9821-7825-3. URL: https://www.simonandschuster.com/books/The-Great-Displacement/Jake-Bittle/9781982178253 (visited on 08/31/2023).

BOE (2021). *Proposition 19 – Board of Equalization*. California State Board of Equalization: Proposition 19. URL: https://www.boe.ca.gov/prop19/#FAQs (visited on 11/23/2022).

Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew Plantinga (2024). *How Are Insurance Markets Adapting to Climate Change? Risk Selection and Regulation in the Market for Homeowners Insurance*. URL: https://papers.ssrn.com/abstract=4881204 (visited on 09/06/2024). Pre-published.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode (2012). "Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century". In: *American Economic Review* 102.3, pp. 238–244. ISSN: 0002-8282. DOI: 10.1257/aer.102.3.238. URL: https://www.aeaweb.org/articles?id=10.1257/aer.102.3.238 (visited on 09/06/2024).

Boustan, Leah Platt, Matthew E. Kahn, Paul W. Rhode, and Maria Lucia Yanguas (2017). *The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data*. w23410. National Bureau of Economic Research. DOI: 10.3386/w23410. URL: https://www.nber.org/papers/w23410 (visited on 03/05/2021).

Bureau, US Census (2021). *California*. California 2010 Census Basic Information. URL: https://www.census.gov/geographies/reference-files/2010/geo/state-local-geo-guides-2010/california.html (visited on 09/18/2024).

– (2022). *Glossary*. Census.gov. URL: https://www.census.gov/programs-surveys/geography/about/glossary.html (visited on 09/18/2024).

– (2023). *ZIP Code Tabulation Areas (ZCTAs)*. Census.gov. URL: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html (visited on 09/18/2024).

CalFire (2024). *CAL FIRE Damage Inspection (DINS) Data - Overview*. ArcGIS: CAL FIRE Damage Inspection (DINS) Data. URL: https://www.arcgis.com/home/item.html?id=994d3dc4569640caadbbc3198d5a3da1 (visited on 09/18/2024).

Callaway, Brantly and Pedro H. C. Sant'Anna (2021). "Difference-in-Differences with Multiple Time Periods". In: *Journal of Econometrics*. Themed Issue: Treatment Effect 1 225.2, pp. 200–230. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2020.12.001. URL: https://www.sciencedirect.com/science/article/pii/S0304407620303948 (visited on 09/16/2024).

CBPC (2020). *Prop. 19 Would Make Changes to California's Residential Property Tax System.* California Budget and Policy Center. URL: https://calbudgetcenter.org/resources/prop-19-would-make-changes-to-californias-residential-property-tax-system/ (visited on 11/23/2022).

CDI (2021). *Wildfire Survivors Now Covered by New Insurance Protections.* California Department of Insurance. URL: https://www.insurance.ca.gov/0400-news/0100-press-releases/2021/release078-2021.cfm (visited on 09/06/2024).

Chase, Jacquelyn and Peter Hansen (2021). "Displacement after the Camp Fire: Where Are the Most Vulnerable?" In: *Society & Natural Resources* 34.12, pp. 1566–1583. ISSN: 0894-1920. DOI: 10.1080/08941920.2021.1977879. URL: https://doi.org/10.1080/08941920.2021.1977879 (visited on 10/14/2025).

Clemens, Jeffrey, Julia A. Payson, and Stan Veuger (2024). *Aid for Incumbents: The Electoral Consequences of COVID-19 Relief.* DOI: 10.3386/w32962. National Bureau of Economic Research: 32962. URL: https://www.nber.org/papers/w32962 (visited on 09/16/2024). Pre-published.

Collins, B. M., M. Kelly, J. W. van Wagtendonk, and S. L. Stephens (2007). "Spatial Patterns of Large Natural Fires in Sierra Nevada Wilderness Areas". In: *Landscape Ecology* 22.4, pp. 545–557. DOI: 10.1007/s10980-006-9047-5. URL: https://pubs.usgs.gov/publication/70029933 (visited on 09/06/2024).

Collins, Brandon, Jay Miller, Andrea Thode, Maggi Kelly, Jan van Wagtendonk, and Scott Stephens (2009). "Interactions Among Wildland Fires in a Long-Established Sierra Nevada Natural Fire Area". In: *Ecosystems* 12, pp. 114–128. DOI: 10.1007/s10021-008-9211-7.

Community Development, Louisiana Office of (2021). *Isle de Jean Charles.* Isle de Jean Charles. URL: https://isledejeancharles.la.gov/ (visited on 11/05/2024).

Contat, Justin, Carrie Hopkins, Luis Mejia, and Matthew Suandi (2024). "When Climate Meets Real Estate: A Survey of the Literature". In: *Real Estate Economics* 52.3, pp. 618–659. ISSN: 1540-6229. DOI: 10.1111/1540-6229.12489. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1540-6229.12489 (visited on 09/25/2025).

Conte, Bruno, Klaus Desmet, and Esteban Rossi-Hansberg (2022). *On the Geographic Implications of Carbon Taxes.* DOI: 10.3386/w30678. National Bureau of Economic Research: 30678. URL: https://www.nber.org/papers/w30678 (visited on 11/14/2023). Pre-published.

CRS (2024). *FEMA's Individuals and Households Program (IHP) - Implementation and Considerations for Congress.* Congressional Research Service. URL: https://sgp.fas.org/crs/homesec/R47015.pdf.

Cruz, José-Luis and Esteban Rossi-Hansberg (2023). "The Economic Geography of Global Warming". In: *Review of Economic Studies.*

Danieli, Oren, Daniel Nevo, Itai Walk, Bar Weinstein, and Dan Zeltzer (2023). *Negative Control Falsification Tests for Instrumental Variable Designs.* arXiv.org. URL: https://arxiv.org/abs/2312.15624v2 (visited on 10/08/2024).

De Chaisemartin, Clément and Xavier D'Haultfoeuille (2022). *Difference-in-Differences Estimators of Intertemporal Treatment Effects*. DOI: 10.3386/w29873. National Bureau of Economic Research: 29873. URL: https://www.nber.org/papers/w29873 (visited on 10/13/2024). Pre-published.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2014). "What Do We Learn from the Weather? The New Climate-Economy Literature". In: *Journal of Economic Literature* 52.3, pp. 740–798. ISSN: 0022-0515. DOI: 10.1257/jel.52.3.740. URL: https://www.aeaweb.org/articles?id=10.1257/jel.52.3.740 (visited on 04/29/2025).

Dennison, Philip E., Simon C. Brewer, James D. Arnold, and Max A. Moritz (2014). "Large Wildfire Trends in the Western United States, 1984–2011". In: *Geophysical Research Letters* 41.8, pp. 2928–2933. ISSN: 0094-8276, 1944-8007. DOI: 10.1002/2014GL059576. URL: https://agupubs.onlinelibrary.wiley.com/doi/10.1002/2014GL059576 (visited on 09/06/2024).

Deryugina, Tatyana (2017). "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance". In: *American Economic Journal: Economic Policy* 9.3, pp. 168–198. ISSN: 1945-7731. DOI: 10.1257/pol.20140296. URL: https://www.aeaweb.org/articles?id=10.1257/pol.20140296 (visited on 07/19/2023).

Deryugina, Tatyana, Laura Kawano, and Steven Levitt (2018). "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns". In: *American Economic Journal: Applied Economics* 10.2, pp. 202–233. ISSN: 1945-7782. DOI: 10.1257/app.20160307. URL: https://www.aeaweb.org/articles?id=10.1257/app.20160307 (visited on 03/05/2021).

Desmet, Klaus, Robert E. Kopp, Scott A. Kulp, Dávid Krisztián Nagy, Michael Oppenheimer, Esteban Rossi-Hansberg, and Benjamin H. Strauss (2021). "Evaluating the Economic Cost of Coastal Flooding". In: *American Economic Journal: Macroeconomics* 13.2, pp. 444–486. ISSN: 1945-7707. DOI: 10.1257/mac.20180366. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20180366 (visited on 09/16/2024).

Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg (2018). "The Geography of Development". In: *Journal of Political Economy* 126.3, pp. 903–983. ISSN: 0022-3808, 1537-534X. DOI: 10.1086/697084. URL: https://www.journals.uchicago.edu/doi/10.1086/697084 (visited on 11/13/2023).

Desmet, Klaus and Esteban Rossi-Hansberg (2015). "On the Spatial Economic Impact of Global Warming". In: *Journal of Urban Economics* 88, pp. 16–37. ISSN: 00941190. DOI: 10.1016/j.jue.2015.04.004. URL: https://linkinghub.elsevier.com/retrieve/pii/S0094119015000339 (visited on 08/31/2023).

– (2024). *Climate Change Economics over Time and Space*. DOI: 10.3386/w32197. National Bureau of Economic Research: 32197. URL: https://www.nber.org/papers/w32197 (visited on 03/04/2024). Pre-published.

DeWaard, Jack, Alexander Din, Kathryn McConnell, and Elizabeth Fussell (2024). "Population Change in Wildfire-Affected Areas in the United States: Evidence from U.S. Postal Service Residential Address Data". In: *Climate and Environmental Changes*. DOI: 10.1007/s11113-024-09904-4. URL: https://knowledgecommons.popcouncil.org/focus_climate-change/35.

DeWaard, Jack, Elizabeth Fussell, Katherine J. Curtis, Stephan D. Whitaker, Kathryn McConnell, Kobie Price, Michael Soto, and Catalina Anampa Castro (2023). "Migration as a Vector of Economic Losses From Disaster-Affected Areas in the United States". In: *Demography* 60.1, pp. 173–199. ISSN: 0070-3370. DOI: 10.1215/00703370-10426100. URL: https://doi.org/10.1215/00703370-10426100 (visited on 07/11/2024).

Dillon, Liam (2020). *Who Wins and Who Loses with California Property Tax Measure Proposition 19*. Los Angeles Times. URL: https://www.latimes.com/homeless-housing/story/2020-10-19/proposition-19-property-tax-ballot-measure-explained-california (visited on 11/23/2022).

Donovan, Victoria M., Raelene Crandall, Jennifer Fill, and Carissa L. Wonkka (2023). "Increasing Large Wildfire in the Eastern United States". In: *Geophysical Research Letters* 50.24, e2023GL107051. ISSN: 1944-8007. DOI: 10.1029/2023GL107051. URL: https://onlinelibrary.wiley.com/doi/abs/10.1029/2023GL107051 (visited on 09/06/2024).

Egan, Patrick J. and Megan Mullin (2017). "Climate Change: US Public Opinion". In: *Annual Review of Political Science* 20 (Volume 20, 2017), pp. 209–227. ISSN: 1094-2939, 1545-1577. DOI: 10.1146/annurev-polisci-051215-022857. URL: https://www.annualreviews.org/content/journals/10.1146/annurev-polisci-051215-022857 (visited on 08/13/2024).

Elliott, James R. and Zheye Wang (2023). "Managed Retreat: A Nationwide Study of the Local, Racially Segmented Resettlement of Homeowners from Rising Flood Risks". In: *Environmental Research Letters* 18.6, p. 064050. ISSN: 1748-9326. DOI: 10.1088/1748-9326/acd654. URL: https://dx.doi.org/10.1088/1748-9326/acd654 (visited on 06/15/2023).

Equifax (2024). *What's the Average Credit Score in Each State? | Equifax*. Equifax. URL: https://www.equifax.com/personal/education/credit/score/articles/-/learn/average-credit-score-state/ (visited on 09/21/2024).

Estes, Becky L., Eric E. Knapp, Carl N. Skinner, Jay D. Miller, and Haiganoush K. Preisler (2017). "Factors Influencing Fire Severity under Moderate Burning Conditions in the Klamath Mountains, Northern California, USA". In: *Ecosphere* 8.5, e01794. ISSN: 2150-8925. DOI: 10.1002/ecs2.1794. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/ecs2.1794 (visited on 09/06/2024).

Farkhondehmaal, Farshad and Navid Ghaffarzadegan (2022). "A Cyclical Wildfire Pattern as the Outcome of a Coupled Human Natural System". In: *Scientific Reports* 12.1, p. 5280. ISSN: 2045-2322. DOI: 10.1038/s41598-022-08730-y. URL: https://www.nature.com/articles/s41598-022-08730-y (visited on 04/01/2024).

FEMA (2003). *A Citizen's Guide to Disaster Assistance*. Emergency Management Institute. URL: https://training.fema.gov/emiweb/downloads/is7unit_3.pdf.

– (2021). *Federal Assistance for California Wildfires Tops $103M | FEMA.Gov*. URL: https://www.fema.gov/press-release/20210223/federal-assistance-california-wildfires-tops-103m (visited on 08/31/2023).

FEMA (2023). *Frequently Asked Questions About FEMA Disaster Assistance | FEMA.Gov*. URL: https://www.fema.gov/fact-sheet/frequently-asked-questions-about-fema-disaster-assistance-1 (visited on 09/06/2024).

– (2024a). *Assistance for Housing and Other Needs | FEMA.Gov*. FEMA. URL: https://www.fema.gov/assistance/individual/housing (visited on 09/21/2024).

– (2024b). *Reforming Individual Assistance: New Benefits and Streamlined Processes to Help Disaster Survivors | FEMA.Gov*. URL: https://www.fema.gov/assistance/individual/2024-reform (visited on 09/06/2024).

Fishback, Price V., Michael R. Haines, and Shawn Kantor (2007). "Births, Deaths, and New Deal Relief during the Great Depression". In: *The Review of Economics and Statistics* 89.1, pp. 1–14. URL: https://ideas.repec.org//a/tpr/restat/v89y2007i1p1-14.html (visited on 09/06/2024).

Flannigan, M. D, B. J Stocks, and B. M Wotton (2000). "Climate Change and Forest Fires". In: *Science of The Total Environment*. Climate Change,Forests And 262.3, pp. 221–229. ISSN: 0048-9697. DOI: 10.1016/S0048-9697(00)00524-6. URL: https://www.sciencedirect.com/science/article/pii/S0048969700005246 (visited on 09/06/2024).

Flavelle, Christopher (2019). "Canada Tries a Forceful Message for Flood Victims: Live Someplace Else". In: *The New York Times. Climate*. ISSN: 0362-4331. URL: https://www.nytimes.com/2019/09/10/climate/canada-flood-homes-buyout.html (visited on 11/05/2024).

Fleck, Robert K. (2001). "Population, Land, Economic Conditions, and the Allocation of New Deal Spending". In: *Explorations in Economic History* 38.2, pp. 296–304. ISSN: 0014-4983. DOI: 10.1006/exeh.2000.0752. URL: https://www.sciencedirect.com/science/article/pii/S0014498300907526 (visited on 09/06/2024).

Frazier, Rex (2021). *California's Ban on Climate-Informed Models for Wildfire Insurance Premiums*. Ecology Law Quarterly. URL: https://www.ecologylawquarterly.org/currents/californias-ban-on-climate-informed-models-for-wildfire-insurance-premiums/ (visited on 08/30/2023).

Fried, Stephie (2022). "Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation". In: *The Review of Economic Studies* 89.6, pp. 3303–3344. ISSN: 0034-6527, 1467-937X. DOI: 10.1093/restud/rdab099. URL: https://academic.oup.com/restud/article/89/6/3303/6484653 (visited on 11/14/2023).

GAO (2020). *Disaster Assistance: Additional Actions Needed to Strengthen FEMA's Individuals and Households Program*. URL: https://www.gao.gov/products/gao-20-503 (visited on 09/06/2024).

Goncalves, A.J. Bento and A.A. Batista Vieira (2015). *Wildland Fires: A Worldwide Reality*.

Goss, Michael, Daniel L. Swain, John T. Abatzoglou, Ali Sarhadi, Crystal A. Kolden, A. Park Williams, and Noah S. Diffenbaugh (2020). "Climate Change Is Increasing the Likelihood of Extreme Autumn Wildfire Conditions across California". In: *Environmental Research Letters* 15.9,

p. 094016. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ab83a7. URL: https://dx.doi.org/10.1088/1748-9326/ab83a7 (visited on 09/06/2024).

Gregory, Jesse (2017). "The Impact of Post-Katrina Rebuilding Grants on the Resettlement Choices of New Orleans Homeowners". In.

Groen, Jeffrey A., Mark J. Kutzbach, and Anne E. Polivka (2019). "Storms and Jobs: The Effect of Hurricanes on Individuals' Employment and Earnings over the Long Term". In: *Journal of Labor Economics* 38.3, pp. 653–685. ISSN: 0734-306X. DOI: 10.1086/706055. URL: https://www.journals.uchicago.edu/doi/abs/10.1086/706055 (visited on 03/08/2021).

Hammer, Roger B., Susan I. Stewart, and Volker C. Radeloff (2009). "Demographic Trends, the Wildland-Urban Interface, and Wildfire Management". In: *Society and Natural Resources. 22: 777-782.* 22, pp. 777–782. DOI: 10.1080/08941920802714042. URL: https://research.fs.usda.gov/treesearch/36418 (visited on 09/20/2024).

Henkel, Marcel, Eunjee Kwon, and Pierre Magontier (2022). *The Unintended Consequences of Post-Disaster Policies for Spatial Sorting.* DOI: 10.2139/ssrn.4237083. URL: https://papers.ssrn.com/abstract=4237083 (visited on 09/06/2024). Pre-published.

Hennighausen, Hannah and Alexander James (2023). *Catastrophic Fires, Human Displacement, and Real Estate Prices in California.* DOI: 10.2139/ssrn.4415542. Social Science Research Network: 4415542. URL: https://papers.ssrn.com/abstract=4415542 (visited on 12/11/2024). Pre-published.

Hsiao, Allan (2023). "Sea Level Rise and Urban Adaptation". In.

Husted, Thomas and David Nickerson (2014). "Political Economy of Presidential Disaster Declarations and Federal Disaster Assistance". In: *Public Finance Review* 42.1, pp. 35–57. ISSN: 1091-1421. DOI: 10.1177/1091142113496131. URL: https://doi.org/10.1177/1091142113496131 (visited on 09/06/2024).

Indaco, Agustín and Francesc Ortega (2023). "Adapting to Climate Risk? Local Population Dynamics in the United States". In.

Issler, Paulo, Richard Stanton, Carles Vergara-Alert, and Nancy Wallace (2020). *Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California.* DOI: 10.2139/ssrn.3511843. URL: https://papers.ssrn.com/abstract=3511843 (visited on 08/31/2023). Pre-published.

– (2024). "Housing and Mortgage Markets with Climate Risk: Evidence from California Wildfires". In.

Jacobson, Lindsey (2024). *Insurers Such as State Farm and Allstate Are Leaving Fire- and Flood-Prone Areas. Home Values Could Take a Hit.* CNBC. URL: https://www.cnbc.com/2024/02/05/what-homeowners-need-to-know-as-insurers-leave-high-risk-climate-areas.html (visited on 06/20/2024).

Jia, Ning, Raven Molloy, Christopher Smith, and Abigail Wozniak (2023). "The Economics of Internal Migration: Advances and Policy Questions". In: *Journal of Economic Literature* 61.1, pp. 144–180. ISSN: 0022-0515. DOI: 10.1257/jel.20211623. URL: https://www.aeaweb.org/articles?id=10.1257/jel.20211623 (visited on 08/31/2023).

Jou, Ariadna and Tommy Morgan (2024). “Do Relief Programs Compensate Affected Populations? Evidence from the Great Depression and the New Deal”. In.

Keeley, Jon E. and Alexandra D. Syphard (2016). “Climate Change and Future Fire Regimes: Examples from California”. In: *Geosciences* 6.3 (3), p. 37. ISSN: 2076-3263. DOI: 10.3390/geosciences6030037. URL: https://www.mdpi.com/2076-3263/6/3/37 (visited on 09/06/2024).

Kestelman, Stephanie (2024). *Environmental Externalities of Urban Growth: Evidence from the California Wildfires*. DOI: 10.2139/ssrn.4629558. URL: https://papers.ssrn.com/abstract=4629558 (visited on 09/16/2024). Pre-published.

Keys, Benjamin J. and Philip Mulder (2024). *Property Insurance and Disaster Risk: New Evidence from Mortgage Escrow Data*. DOI: 10.3386/w32579. National Bureau of Economic Research: 32579. URL: https://www.nber.org/papers/w32579 (visited on 06/17/2024). Pre-published.

Kimberlin, Sara and Kayla Kitson (2020). *Prop. 19 Would Make Changes to California's Residential Property Tax System*. California Budget and Policy Center. URL: https://calbudgetcenter.org/resources/prop-19-would-make-changes-to-californias-residential-property-tax-system/ (visited on 10/30/2024).

Kleinman, Benny, Ernest Liu, and Stephen J. Redding (2023). “Dynamic Spatial General Equilibrium”. In: *Econometrica* 91.2, pp. 385–424. ISSN: 0012-9682. DOI: 10.3982/ECTA20273. URL: https://www.econometricsociety.org/doi/10.3982/ECTA20273 (visited on 11/13/2023).

Lapinski, Paul, Peter Manning, Roozbeh Moghadam, Jacob Morris, and Till von Wachter (2025). “Unemployment Insurance Claims After the LA Wildfires”. In.

Lara, Ricardo (2019). “Deduction of Land Value after Wildfires When the Insured Replaces the Destroyed Home with an Already Built Home at a New Location”. In.

LendEDU (2017). *Which Degrees Produce The Most And Least Financially Responsible Graduates?* Forbes. URL: https://www.forbes.com/sites/priceonomics/2017/02/28/which-college-degrees-produce-the-most-and-least-financially-responsible-students/ (visited on 11/06/2024).

Lunney, Kellie (2014). *FEMA Spent Billions on Disaster Assistance Overhead During the Last Decade*. Government Executive. URL: https://www.govexec.com/management/2014/12/fema-spent-billions-disaster-assistance-overhead-during-last-decade/101619/ (visited on 09/10/2024).

Lynch, Kenneth (2020). “More About Census Blocks”. In: URL: https://transition.fcc.gov/form477/Geo/more_about_census_blocks.pdf.

McCaffrey, Sarah, Robyn Wilson, and Avishek Konar (2018). “Should I Stay or Should I Go Now? Or Should I Wait and See? Influences on Wildfire Evacuation Decisions”. In: *Risk Analysis* 38.7, pp. 1390–1404. ISSN: 1539-6924. DOI: 10.1111/risa.12944. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/risa.12944 (visited on 10/28/2024).

McConnell, Kathryn, Elizabeth Fussell, Jack DeWaard, Stephan Whitaker, Katherine J. Curtis, Lise St. Denis, Jennifer Balch, and Kobie Price (2024). “Rare and Highly Destructive Wildfires Drive Human Migration in the U.S.” In: *Nature Communications* 15.1, p. 6631. ISSN: 2041-1723.

DOI: 10.1038/s41467-024-50630-4. URL: https://www.nature.com/articles/s41467-024-50630-4 (visited on 09/20/2024).

McConnell, Kathryn, Stephan D. Whitaker, Elizabeth Fussell, Jack DeWaard, Katherine Curtis, Kobie Price, Lise St. Denis, and Jennifer Balch (2021). "Effects of Wildfire Destruction on Migration, Consumer Credit, and Financial Distress". In: *Working Paper* 21–29. DOI: 10.26509/frbc-wp-202129. URL: https://www.clevelandfed.org/publications/working-paper/2021/wp-2129-effects-of-wildfire-destruction-on-migration (visited on 08/29/2023).

McCoy, Shawn J. and Randall P. Walsh (2018). "Wildfire Risk, Salience & Housing Demand". In: *Journal of Environmental Economics and Management* 91.C, pp. 203–228. URL: https://ideas.repec.org/a/eee/jeeman/v91y2018icp203-228.html (visited on 07/27/2022).

Mueller, Stephanie E., Andrea E. Thode, Ellis Q. Margolis, Larissa L. Yocom, Jesse D. Young, and Jose M. Iniguez (2020). "Climate Relationships with Increasing Wildfire in the Southwestern US from 1984 to 2015". In: *Forest Ecology and Management* 460, p. 117861. ISSN: 0378-1127. DOI: 10.1016/j.foreco.2019.117861. URL: https://www.sciencedirect.com/science/article/pii/S0378112719314744 (visited on 09/06/2024).

NIST (2019). *Damage Data | NIST*. National Institute of Standards and Technology, U.S. Department of Commerce. URL: https://www.nist.gov/el/fire-research-division-73300/wildland-urban-interface-fire-73305/nist-investigation-california-1 (visited on 09/18/2024).

OCHA (2024). *2023 Disasters in Numbers*. United Nations Office for the Coordination of Humanitarian Affairs (OCHA). URL: https://reliefweb.int/report/world/2023-disasters-numbers (visited on 09/05/2024).

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan I. Stewart (2018). "Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk". In: *Proceedings of the National Academy of Sciences* 115, pp. 3314–3319. DOI: 10.1073/pnas.1718850115. URL: https://research.fs.usda.gov/treesearch/55817 (visited on 09/06/2024).

Rao, Krishna, A. Park Williams, Noah S. Diffenbaugh, Marta Yebra, and Alexandra G. Konings (2022). "Plant-Water Sensitivity Regulates Wildfire Vulnerability". In: *Nature Ecology & Evolution* 6.3, pp. 332–339. ISSN: 2397-334X. DOI: 10.1038/s41559-021-01654-2. URL: https://www.nature.com/articles/s41559-021-01654-2 (visited on 09/06/2024).

Reeves, Andrew (2011). "Political Disaster: Unilateral Powers, Electoral Incentives, and Presidential Disaster Declarations". In: *The Journal of Politics* 73.4, pp. 1142–1151. ISSN: 0022-3816. DOI: 10.1017/s0022381611000843. JSTOR: 10.1017/s0022381611000843. URL: https://www.jstor.org/stable/10.1017/s0022381611000843 (visited on 05/20/2024).

Rossiter, Katy (2011). *What Are Census Blocks?* Census.gov. URL: https://www.census.gov/newsroom/blogs/random-samplings/2011/07/what-are-census-blocks.html (visited on 09/18/2024).

Roth, Jonathan (2022). "Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends". In: *American Economic Review: Insights* 4.3, pp. 305–322. ISSN: 2640-205X, 2640-2068. DOI: 10.1257/aeri.20210236. URL: https://pubs.aeaweb.org/doi/10.1257/aeri.20210236 (visited on 09/16/2024).

Roth, Jonathan, Pedro H.C. Sant'Anna, Alyssa Bilinski, and John Poe (2023). "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature - ScienceDirect". In: *Journal of Econometrics* 235.2, pp. 2218–2244. URL: https://www.sciencedirect.com/science/article/pii/S0304407623001318 (visited on 09/12/2024).

Schubert, Gregor (2024). "House Price Contagion and U.S. City Migration Networks". In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.4984580. URL: https://www.ssrn.com/abstract=4984580 (visited on 10/30/2024).

Sharygin, Ethan (2021). "Estimating Migration Impacts of Wildfire: California's 2017 North Bay Fires". In: *The Demography of Disasters: Impacts for Population and Place*. Ed. by Dávid Karácsonyi, Andrew Taylor, and Deanne Bird. Cham: Springer International Publishing, pp. 49–70. ISBN: 978-3-030-49920-4. DOI: 10.1007/978-3-030-49920-4_3. URL: https://doi.org/10.1007/978-3-030-49920-4_3 (visited on 10/14/2025).

Sheldon, Tamara L. and Crystal Zhan (2022). "The Impact of Hurricanes and Floods on Domestic Migration". In: *Journal of Environmental Economics and Management* 115, p. 102726. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2022.102726. URL: https://www.sciencedirect.com/science/article/pii/S009506962200081X (visited on 01/27/2023).

Thompson, Jonathan R. and Thomas A. Spies (2009). "Vegetation and Weather Explain Variation in Crown Damage within a Large Mixed-Severity Wildfire". In: *Forest Ecology and Management* 258.7, pp. 1684–1694. ISSN: 0378-1127. DOI: 10.1016/j.foreco.2009.07.031. URL: https://www.sciencedirect.com/science/article/pii/S0378112709005040 (visited on 09/06/2024).

Wendland, Tegan (2019). *Coastal News Roundup: An Update On Isle de Jean Charles*. WWNO. URL: https://www.wwno.org/coastal-desk/2019-01-25/coastal-news-roundup-an-update-on-isle-de-jean-charles (visited on 11/05/2024).

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam (2006). "Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity". In: *Science* 313.5789, pp. 940–943. DOI: 10.1126/science.1128834. URL: https://www.science.org/doi/full/10.1126/science.1128834 (visited on 09/06/2024).

WFCA (2024). *History of California Wildfires*. URL: https://wfca.com/wildfire-articles/history-of-california-wildfires/ (visited on 09/05/2024).

Wing, Coady, Seth M Freedman, and Alex Hollingsworth (2024). "Stacked Difference-in-Differences". In: *NBER Working Papers*.

Winkler, Richelle L. and Mark D. Rouleau (2021). "Amenities or Disamenities? Estimating the Impacts of Extreme Heat and Wildfire on Domestic US Migration". In: *Population and Environment* 42.4, pp. 622–648. ISSN: 0199-0039, 1573-7810. DOI: 10.1007/s11111-020-00364-4. URL: https://link.springer.com/10.1007/s11111-020-00364-4 (visited on 09/06/2024).

Wright, Gavin (1974). "The Political Economy of New Deal Spending". In: *The Review of Economics and Statistics* 56, pp. 30–38. DOI: 10.2307/1927524.

Yadav, Kamini, Francisco J. Escobedo, Alyssa S. Thomas, and Nels G. Johnson (2023). "Increasing Wildfires and Changing Sociodemographics in Communities across California, USA". In: *International Journal of Disaster Risk Reduction* 98, p. 104065. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2023.104065. URL: https://www.sciencedirect.com/science/article/pii/S2212420923005459 (visited on 05/30/2025).

Yagan, Danny (2019). "Employment Hysteresis from the Great Recession". In: *Journal of Political Economy* 127.5, pp. 2505–2558. ISSN: 0022-3808. DOI: 10.1086/701809. URL: https://www.journals.uchicago.edu/doi/full/10.1086/701809 (visited on 02/23/2023).

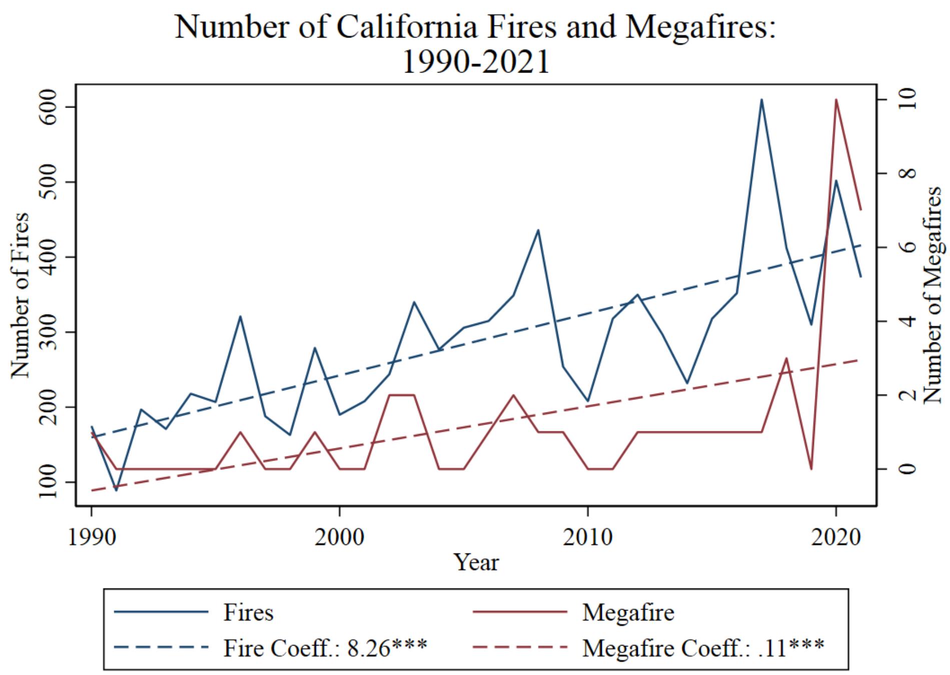
Yao, Alain N., Montfort Kabundi, and Jiaxiong Mlachila (2023). *How Persistent Are Climate-Related Price Shocks? Implications for Monetary Policy*. IMF. URL: https://www.imf.org/en/Publications/WP/Issues/2022/10/28/How-Persistent-are-Climate-Related-Price-Shocks-Implications-for-Monetary-Policy-525048 (visited on 08/27/2023).

Zabek, Mike (2024). "Local Ties in Spatial Equilibrium". In: *American Economic Journal: Macroeconomics* 16.2, pp. 287–317. ISSN: 1945-7707. DOI: 10.1257/mac.20210326. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20210326 (visited on 10/13/2024).

Figures

Figures

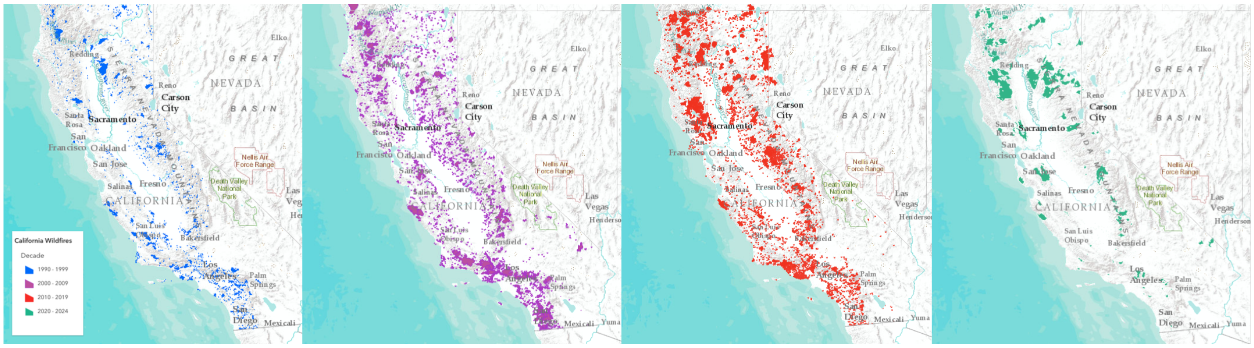
Figure 1: The number of California fires and megafires have been increasing over the past three decades.



Notes: The California fires data comes from CAL FIRE. The original data spans from 1900-2021, though the data quality increases after the 1950s. From 1990-2021, each year is associated with 8.26 additional fires. There has also been an increase in megafires, which are fires that burned over 100,000 acres. Though the number increase is small, the destruction from each megafire is substantial. There was an extraordinary number of megafires in 2020, though even before then, there was a slight increase in the number of expected megafires as well.

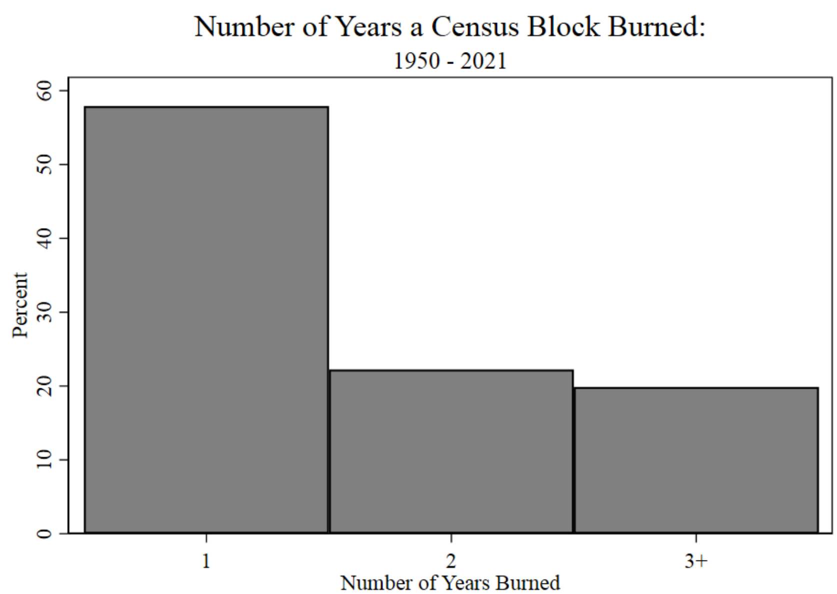
Figure 2: California wildfires reburn the same areas and burn new areas over time.

(a) Map of Fires in California (2000-2021)



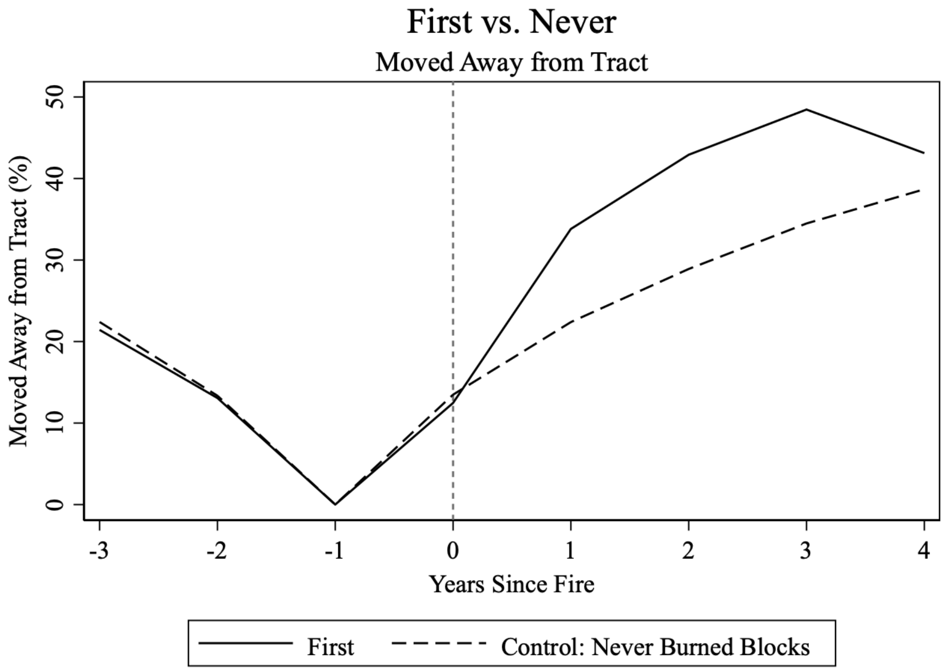
Notes: This map shows the areas that are burned in California throughout the decades, beginning in the 1990s (blue), 2000s (purple), 2010s (red), and 2020-2024 (green). Source: CAL FIRE Historical Wildfires Data and created in ArcGIS.

(b) Number of Years a Census Block Burned (1950-2021)



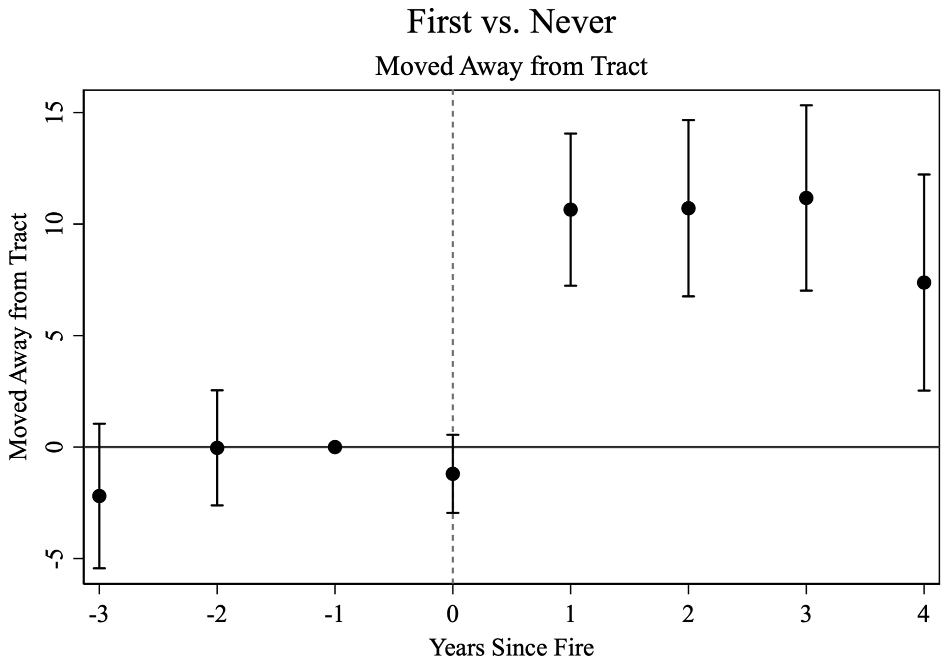
Notes: This graph shows the percent of census blocks that have burned by a fire for one, two, or three or more years. Of the sample of census blocks that have ever burned from 1950-2021, the majority (almost 60%) have burned only once during this time period. Around 20% have burned twice. The remaining 20% that have burned more than three times shows that certain blocks face repeated wildfire risk. The data is from Cal Fire.

Figure 3: There is a similar likelihood of moving away between the treated vs. control groups before the first fire.



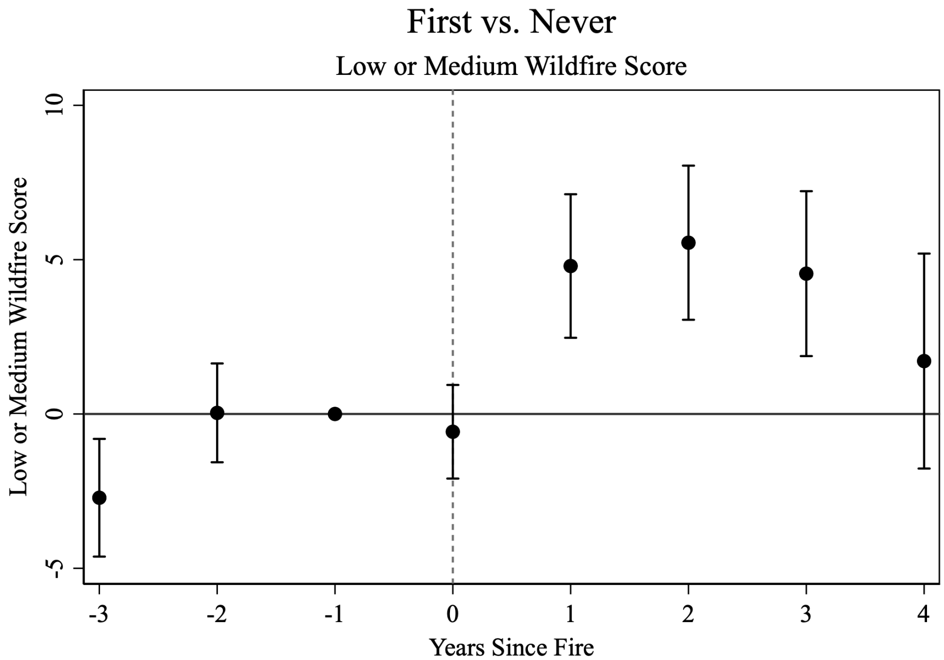
Notes: This graph shows the percent of individuals that are at a different tract than where they were the year before the first fire ("Moved Away from Tract") for the treated and the control groups using the UCCCP data. The treated group consists of individuals living in blocks that are burned for the first time. The control group consists of those living within the same census tract as the first burned blocks, but they are living in blocks that are never burned. The time is standardized to be relative to the year of the first fire that impacted the block. Before the fire (i.e. time 0), the migration rates are the same and parallel, giving powerful strength to the identification strategy. The decrease in year four for the treated group is suggestive evidence that individuals are returning to the tract after moving away.

Figure 4: Individuals in blocks that burn for the first time are more likely to move and to stay away after the first burn.



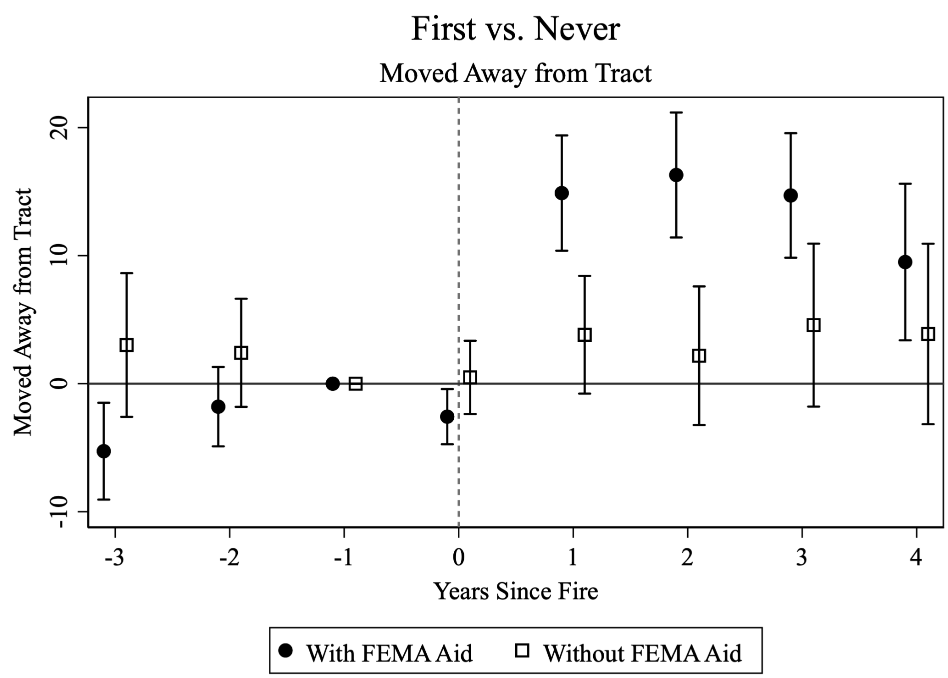
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 using the UCCCP data from 2014-2021. The outcome variable is an indicator variable that equals one if the individual is at a different tract than where they were the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect sustains to four years after the fire. Figure 3 shows suggestive evidence that the dip in the fourth year is from those in the burned blocks moving back.

Figure 5: Individuals in blocks that burn for the first time are more likely to move to safe areas after the first burn, though the effect dissipates by the fourth year.



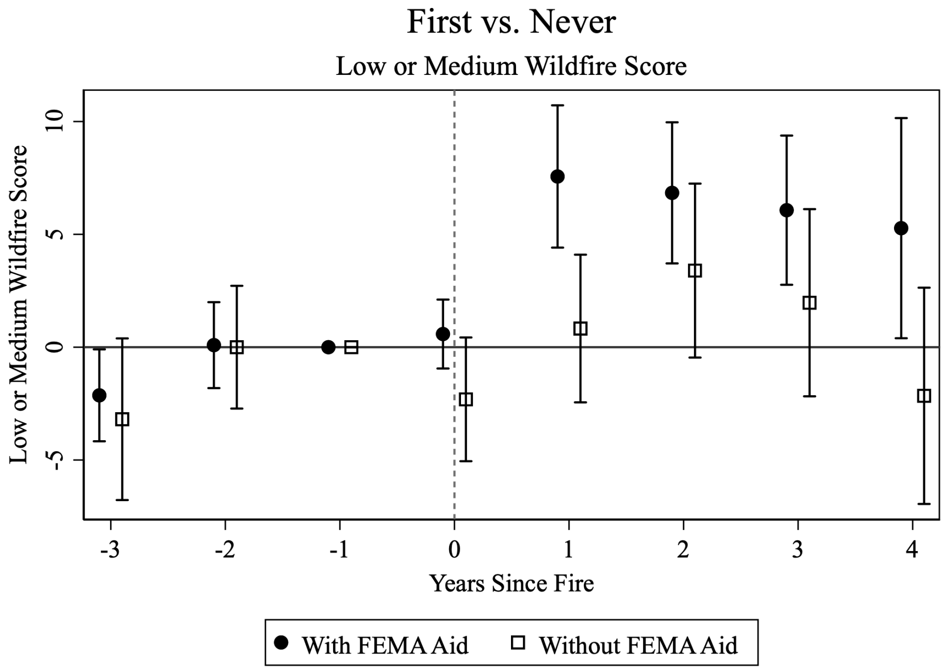
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 using the UCCCP data from 2014-2021. The outcome variable is an indicator variable that equals one if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), which is defined using FEMA's wildfire risk index that ranges from 0-100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of being in a safe tract after the fire, though the effect dissipates four years after the fire.

Figure 6: Receiving government aid is associated with a higher likelihood of moving away.



Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 using the UCCCP data from 2014-2021, separately for first fires that receive FEMA Individuals and Households Program aid and first fires that do not. The outcome variable is an indicator variable that equals one if the individual is at a different tract than where they were the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. Individuals that experience first fires that receive aid are more likely to move away, whereas those that experience first fires that do not receive aid have no migration effects. This is correlational evidence of the effect of aid on migration.

Figure 7: Receiving government aid is associated with a higher likelihood of moving to a safe area, though not as much as a random mover.



Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 using the UCCCP data from 2014-2021, separately for first fires that receive FEMA Individuals and Households Program aid and first fires that do not. The outcome variable is an indicator variable that equals one if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), which is defined using FEMA's wildfire risk index that ranges from 0-100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. Individuals that experience first fires that receive aid are more likely to be in safe areas, even four years after the fire, whereas those that experience first fires that do not receive aid are not. This is correlational evidence of the effect of aid on migration.

Tables

Table 1: First vs. Never Burned Summary Statistics

	Treated		Control			
			Mean	SD	Mean	SD
Difference	p-value					
Demographic Characteristics						
Age	52.81	(18.26)	50.94	(18.08)	1.86	0.00
Male	0.50	(0.50)	0.50	(0.50)	-0.00	0.82
Married	0.63	(0.48)	0.63	(0.48)	-0.01	0.59
College	0.68	(0.47)	0.64	(0.48)	0.04	0.01
Duration	1.82	(1.55)	1.70	(1.78)	0.12	0.02
Moved within Year						
Tract	12.33	(32.89)	13.04	(33.68)	-0.71	0.48
County	5.34	(22.48)	5.57	(22.94)	-0.24	0.73
State	1.84	(13.45)	1.61	(12.57)	0.23	0.57
Tract Characteristics						
Wildfire Risk Score	81.86	(30.56)	76.35	(32.24)	5.51	0.00
Overall Risk Score	79.32	(15.81)	79.51	(19.44)	-0.19	0.69
Expected Annual Loss Score	80.13	(16.42)	80.25	(18.88)	-0.12	0.81
Number of Insurance Providers	59.95	(9.20)	60.23	(11.13)	-0.29	0.40
Percent FAIR Policies	0.74	(1.21)	0.52	(1.10)	0.23	0.00
Financial Characteristics						
Credit Score	701.30	(115.15)	694.48	(122.24)	6.81	0.05
Number of Open Credit Cards	2.44	(2.88)	2.54	(3.02)	-0.10	0.25
Total Credit Limit	21,145.96	(23,184.96)	20,486.56	(22,966.83)	659.41	0.44
Total Payment	1,314.02	(2,243.73)	1,278.34	(5,915.75)	35.68	0.67
Number of Open Loans	4.50	(4.43)	4.55	(4.51)	-0.05	0.74
Number of Open Auto Loans	0.32	(0.60)	0.33	(0.60)	-0.01	0.57
Has Mortgage Loans	0.29	(0.46)	0.28	(0.45)	0.01	0.47
Bankruptcy	4.69	(21.16)	4.67	(21.09)	0.03	0.97
Number of Current Delinquencies	0.07	(0.36)	0.07	(0.42)	0.01	0.50

Notes: This table reports the average and standard deviation for a variety of characteristics separately for the treated and control groups. The treated group consists of individuals living in census blocks burned for the first time. The control group consists of people living within the same census tract as the first-burned blocks but in census blocks that are never burned. Demographic characteristics, migration outcomes, and financial characteristics come from the UCCCP data. The tract characteristics come from the FEMA wildfire risk index and California Department of Insurance (CDI).

Table 2: Percentage of Population That Moves by Fire Type

(a) First vs. Never

	First vs. Never		With Aid vs. Never		Without Aid vs. Never	
	Treatment	Control	Treatment	Control	Treatment	Control
Different Tract						
Year After Fire	23.10	13.74	28.99	13.29	14.73	14.07
Four Years After Fire	44.21	37.07	45.56	36.65	41.88	37.08
Returned to Tract of Fire						
Four Years Later	4.51	1.63	5.93	1.44	2.09	1.73
Moved Year of Fire, Returned Four Years Later	19.63	12.32	21.62	11.31	12.50	12.68

(b) Megafire vs. Never

	Megafire vs. Never		With Aid vs. Never		Without Aid vs. Never	
	Treatment	Control	Treatment	Control	Treatment	Control
Different Tract						
Year After Fire	26.52	11.59	26.35	11.91	27.78	11.14
Four Years After Fire	39.59	31.01	39.86	30.15	36.84	33.33
Returned to Tract of Fire						
Four Years Later	3.05	1.42	1.45	1.25	7.02	1.16
Moved Year of Fire, Returned Four Years Later	12.77	14.29	6.67	12.77	25.00	11.54

Notes: This table reports the percentage of the population that I observe in the UCCCP data in a different census tract or returned to the census tract of the fire at different points in time after the fire. Panel (a) refers to people living in census blocks burned for the first time and people living within the same census tract as the first-burned blocks but in blocks that are never burned. Panel (b) refers to people living in census blocks burned by a megafire and people living within the same census tract as the megafire-burned blocks but in blocks that are never burned. The "Different Tract" category reflects the percentage of people whom I observe in the data in a different tract from where they were the year before the fire at two points in time: one year after the fire and four years after the fire. The "Returned to Tract" category reflects the percentage of people whom I observe in the data who moved away (i.e., are observed in a different tract) but then came back to the tract they were in the year before the fire. The "Four Years Later" variable includes the percentage of the total population who moved away and then returned. The "Moved Year of Fire, Returned Four Years Later" variable includes the percentage of people who moved away the year of the fire but had returned by four years after the fire.

Table 4: Politically Competitive vs. Politically Noncompetitive County Summary Statistics: 2000-2021

	<5%		>5%			
	Mean	SD	Mean	SD	Difference	p-value
Area Characteristics						
Total Voters	252,300	(282,937)	223,150	(486,939)	29,150	0
Experienced Fire	0.84	(0.37)	0.75	(0.43)	0.09	0.01
Experienced Megafire	0.24	(0.43)	0.30	(0.46)	-0.06	0.17
Number of Fires	7.21	(8.62)	7.55	(10.51)	-0.34	0.71
Number of Megafires	0.11	(0.35)	0.07	(0.31)	0.04	0.28
Average Fire	8.07	(37.92)	5.55	(26.66)	2.52	0.48
Burned Total	45.15	(148.87)	29.10	(122.48)	16.05	0.26
Largest Fire	33.74	(116.71)	22.25	(91.46)	11.50	0.30
Aid Characteristics						
IHP Aid	0.12	(0.32)	0.04	(0.20)	0.08	0.01
IHP Aid per Capita	9.78	(81.92)	1.40	(16.69)	8.38	0.27
Total Approved IHP Aid	1,069,911	(8,012,799)	81,232	(715,451)	988,679	0
Total	119		1,157			
IHP Aid if Fire	0.14	(0.35)	0.05	(0.23)	0.09	0.02
IHP Aid per Capita if Fire	11.64	(89.32)	1.87	(19.26)	9.77	0.28
Total Burned by Fire	100		867			
IHP Aid if Megafire	0.28	(0.45)	0.07	(0.25)	0.21	0.02
IHP Aid per Capita if Megafire	38.01	(164.75)	2.17	(20.51)	35.84	0.25
Total Burned by Megafire	29		349			
Log IHP Aid per Capita	1.83	(2.80)	1.36	(2.40)	0.48	0.58
Percent Approved for FEMA Aid	16.11	(10.17)	13.99	(12.22)	2.12	0.52
Total Received IHP	14		47			

Notes: This table reports summary statistics for counties that are politically competitive vs. those that are not. I define a politically competitive county as one in which the difference in the vote share between the top two candidates in the most recent presidential election is less than 5%. I use data from MIT Election Labs to define the vote shares. The area characteristics are calculated from data from CAL FIRE, with the exception of Total Voters, which comes from MIT Election Labs. The aid characteristics are calculated from FEMA's Housing Assistance Program Data, combining the Owners and Renters data. There are 58 counties in California, and there were six presidential elections between 2000 and 2021. For the election years in this time period, there are 32 county-years that are politically competitive, including 18 unique counties and 9 counties that are politically competitive for more than one election.

Table 5: First Stage: Politically Competitive 2014-2021

	Post × Treated × IHP
Post × Treated × Political Competitiveness ($< 5\%$)	0.329***
	(0.076)
Post × Treated	0.610***
	(0.068)
R-squared	0.616
N	288,299
Mean	0.228
F-stat	58.02
Controls	Yes
Relative Time FE	Yes
Calendar Year FE	Yes
Individual FE	Yes
Cluster	County

Notes: I instrument receipt of any FEMA Individuals and Households Program (IHP) aid by political competitiveness. I define a politically competitive county as one in which the difference in the vote share is within five percent ($< 5\%$). I use data from MIT Election Labs to define the vote shares. I estimate Equation 7 using UCCCP data from 2014 to 2021. I include the average size of the fires within the county (in thousands of acres), the age category of the individual, whether she is married, whether she has a college education, and the duration of time she lives in the census block as controls. I also include relative year, calendar year, and individual fixed effects. I cluster the regression at the county level.

Table 6: Exclusion Restriction: Politically Competitive Counties and Spending

	Fire		< 5%		Fire x < 5%		
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Time Frame
Expenditures ($)							
Total	393,727,240	0.001	174,315,184	0.491	-266,342,283	0.312	2003-2019
General	20,403,124	0.005	3,539,983	0.820	1,543,792	0.933	2003-2019
Health	28,135,304	0.077	82,868,661	0.228	-65,642,667	0.328	2003-2019
Public Assistance	129,160,127	0.000	103,394,595	0.114	-110,227,330	0.112	2003-2019
Fire Spending	7,454,573	0.005	-2,836,463	0.009	14,079,207	0.009	2003-2019
Food Stamps							
Households	114,405	0.000	141,937	0.012	-77,897	0.221	2003-2018
Benefits ($)	35,133,306	0.000	44,845,163	0.009	-15,849,734	0.434	2003-2018
Value ($)	35,088,473	0.000	45,048,065	0.009	-15,940,276	0.428	2003-2018
Medi-Cal							
Renewals Due	19,726	0.326	-83,609	0.006	-10,214	0.638	2018-2021
Continued	5,486	0.783	-50,578	0.026	-12,837	0.526	2018-2021
Reinstated	4,340	0.111	-878	0.443	-4,166	0.115	2018-2021
Taxes							
Collected	1,524,605	0.470	-11,285,056	0.010	778,062	0.883	2012-2018

Notes: The exclusion restriction requires that a county's political competitiveness impact migration through only aid receipt, nothing else. Although this condition is not directly testable, I evaluate the likelihood of increased expenditures, non-FEMA government aid, and tax amounts as a way of assessing the validity of the exclusion restriction. I define a politically competitive county as one in which the difference in the vote share between the top two candidates in the most recent presidential election is within 5%. I use data from MIT Election Labs to define vote shares. I estimate Equation 8 using a variety of county-level data sources from the California Open Data website. The expenditures data come from California's County Financial Transactions Report on Expenditures. The food stamps data come from CalFresh, California's implementation of the Supplemental Nutrition Assistance Program (SNAP). The data for Medi-Cal (California's version of Medicaid) come from California Health and Human Services. The tax data come from the California Department of Tax and Fee Administration. I find that politically competitive counties that experience a fire only have higher fire-related spending, which is consistent with what my instrument is intended to capture.

Table 7: DID and DID IV Results: Political Competitiveness (< 5%)

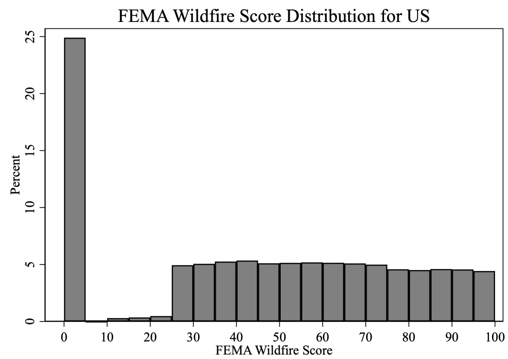
	DID		DID IV	
	Moved Away from Tract	Low or Medium Wildfire Risk Tract	Moved Away from Tract	Low or Medium Wildfire Risk Tract
Post × Treated × IHP	18.898***	7.714**	35.170***	-0.540
	(2.711)	(1.893)	(8.762)	(8.923)
Post × Treated	-2.651	-0.685	-14.195**	4.577
	(2.044)	(1.457)	(7.928)	(4.686)
N	250,594	288,299	250,594	288,299
Mean	17.40	22.23	17.40	22.23
First Stage F-stat			17.18	18.92
Controls	Yes	Yes	Yes	Yes
Relative Year FE	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

Notes: This table reports the coefficients from the difference-in-differences (DID) specification, which estimates Equation 6, and the DID instrumental variables specification (DID IV), which first estimates Equation 7 for FEMA Individuals and Households Program (IHP) aid. In both specifications, I control for the average size of the fires within the county (in thousands of acres), the age category of the individual, whether she is married, whether she has a college education, and the duration of time she lives in the census block. I also include relative year, calendar year, and individual fixed effects. I cluster the regression at the county level.

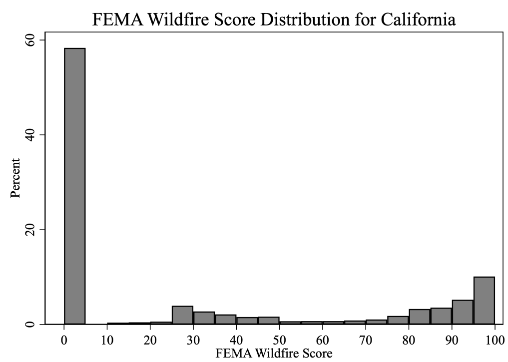
A Appendix Figures

Figure A1: FEMA Wildfire Score Distribution

(a) FEMA Wildfire Score Distribution for the United States



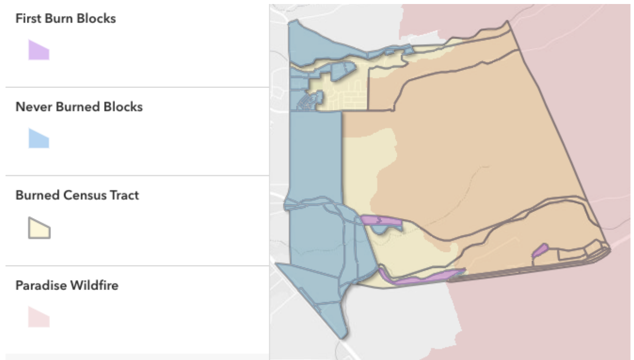
(b) FEMA Wildfire Score Distribution for California



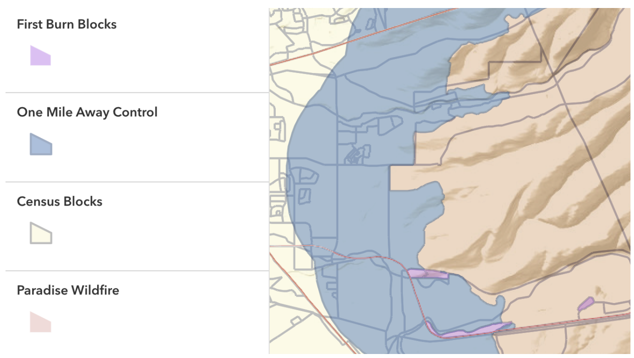
Notes: These graphs shows the wildfire score distribution for the United States and California. The data are from FEMA and list the wildfire risk score at the census tract level. This is a one-year measure of wildfire risk, defined at the year 2021. Figure A1 suggests that the wildfire risk score in the United States overall is roughly uniform when considering the tracts with a score lower than 25 as one entity (i.e., <25, or "Low Wildfire Risk"). Figure A1(b) suggests that the wildfire risk score in California is not uniform but skewed to the left, with a higher proportion of tracts with minimal wildfire risk. This may seem surprising but is likely due to California's large surface area and the fact that most of the state is not at the wildland-urban interface. There is also a larger proportion of tracts that are "Very High Wildfire Risk" (i.e., >75) in California than in the United States overall.

Figure A2: Map Example of Treatment vs. Control Groups

(a) Map Example of First Burn vs. Never Burned



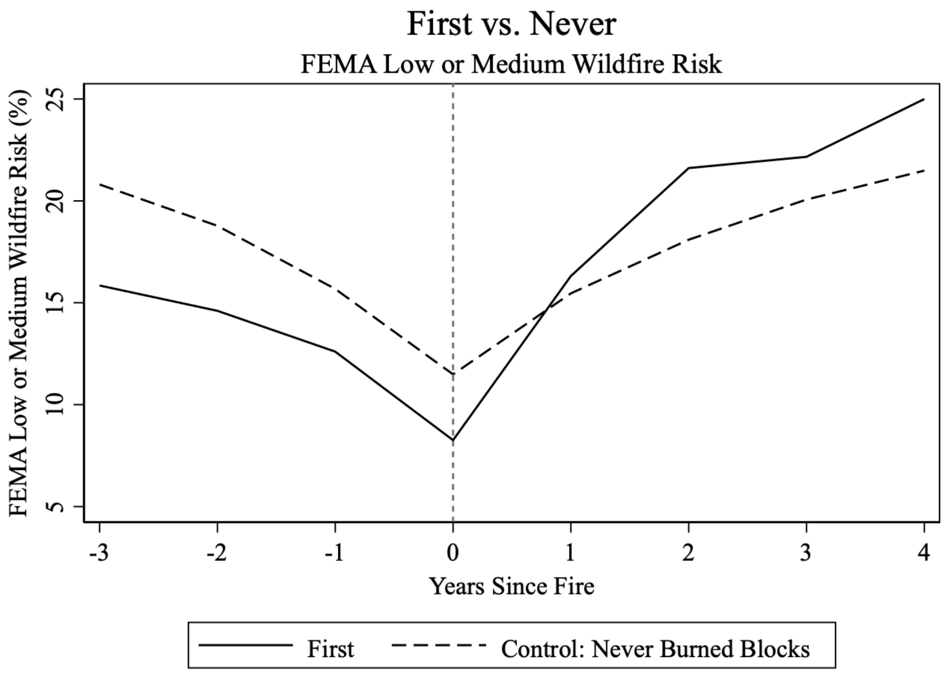
(b) Map Example of First Burn vs. Within One Mile Away



(c) Map Example of First Burn vs. One to Five Miles Away

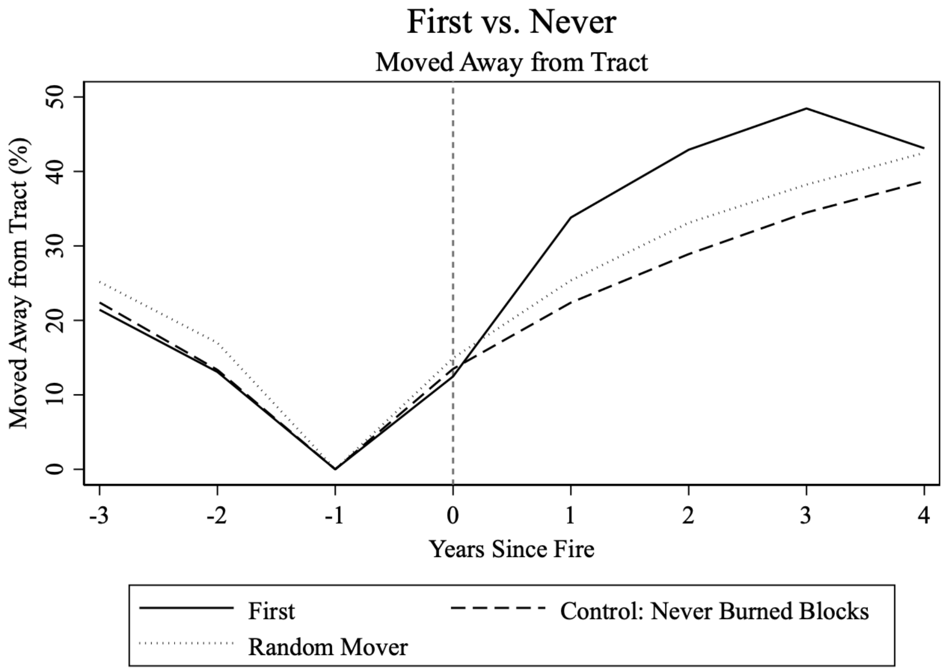
Notes: These maps show an example of the treatment and various control groups used in the analysis. The purple area represents the census blocks that are burned for the first time (in this case, by the Paradise Fire). The blue area denotes the various definitions of the control groups: blocks that are never burned but within a census tract that has a block that is burned for the first time, blocks within the one mile perimeter of the fire that burns a block for the first time, and blocks within a one- to five-mile perimeter of that fire.

Figure A3: Parallel Trends in Low or Medium Wildfire Risk Before First Fire



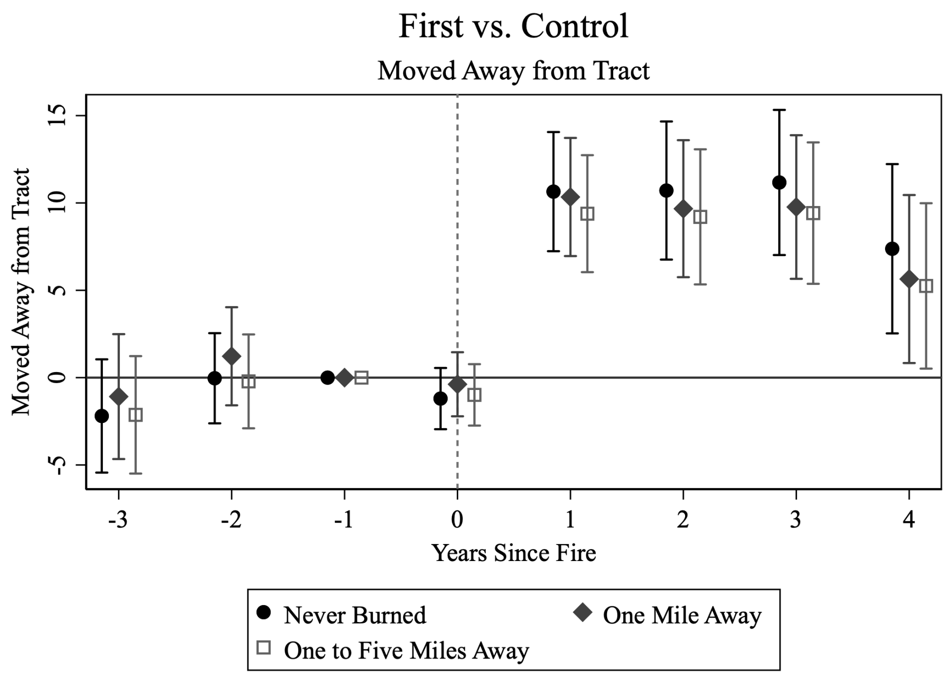
Notes: This graph shows the percentage of individuals in a low- or medium-wildfire-risk census tract for the treated and control groups using the UCCCP data. The wildfire risk data come from FEMA. The treated group consists of individuals living in blocks that are burned for the first time. The control group consists of people living within the same census tract as the first-burned blocks but in blocks that are never burned. The time is standardized to be relative to the year of the first fire that impacted the block. Before the fire (i.e. time 0), the wildfire risks are parallel, giving credibility to this empirical strategy. They are not identical because the control group is defined separately for each fire, so there could be individuals within the control group who are represented multiple times in the dataset. For instance, it could be that a relatively safe census tract has multiple census blocks within it that are burned for the first time, and people in the control group areas with a lower wildfire risk score are counted multiple times, raising the proportion of people in low- or medium-wildfire-risk tracts for the control group.

Figure A4: There is a similar likelihood of moving away between the treated vs. control groups before the first fire, which is lower than the average mover.



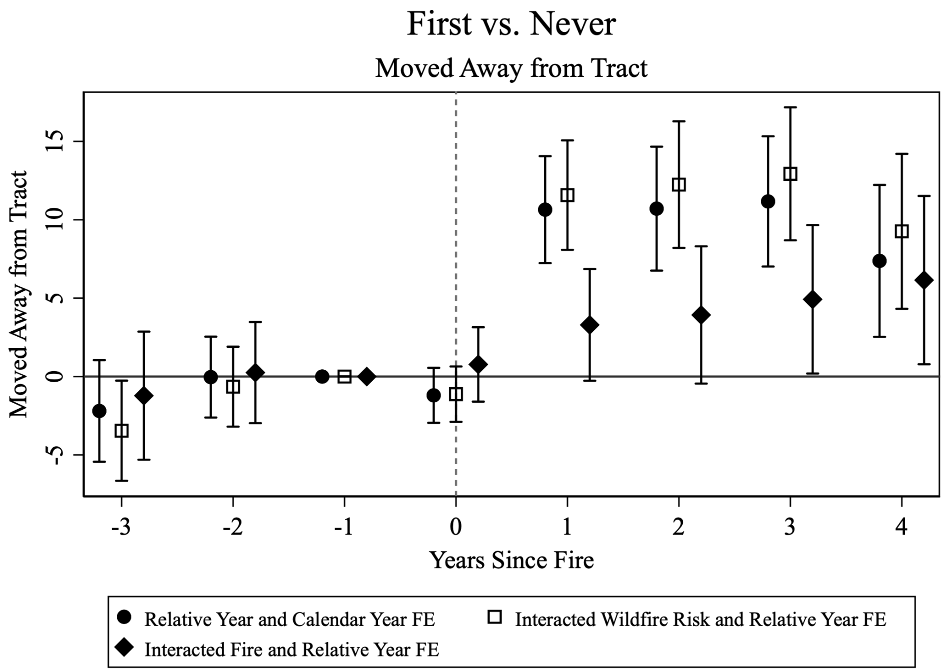
Notes: This graph shows the percent of individuals that are at a different tract than where they were the year before the first fire ("Moved Away from Tract") for the treated and the control groups, as well as a 1% random sample of everyone who has ever lived in California. The treated group consists of individuals living in blocks that are burned for the first time. The control group consists of those living within the same census tract as the first burned blocks, but they are living in blocks that are never burned. The time is standardized to be relative to the year of the first fire that impacted the block. Before the fire (i.e. time 0), the migration rates are the same and parallel, giving powerful strength to the identification strategy. The migration rate is lower than the random sample of everyone who has ever lived in California, which suggests the people who choose to live in census tracts that burn are a selected sample with lower likelihood of migration. The decrease in year four for the treated group is suggestive evidence that individuals are returning to the tract after moving away.

Figure A5: Similar Likelihood of Moving Away from the Burned Tract After First Burn across Control Groups



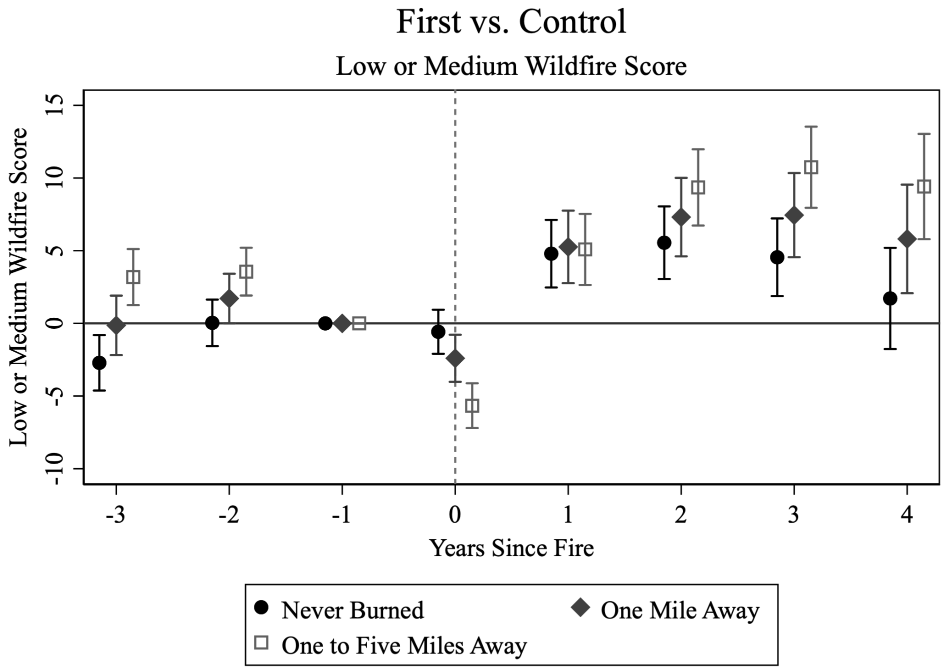
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 and with different control groups. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of an individual's likelihood of moving away starting the year after the fire, and this effect persists for four years after the fire. Figure 3 shows suggestive evidence that the dip in the fourth year is from people in the burned blocks moving back.

Figure A6: Similar Likelihood of Longer-Term Moving Away from Burned Tract After First Burn Across Empirical Specifications



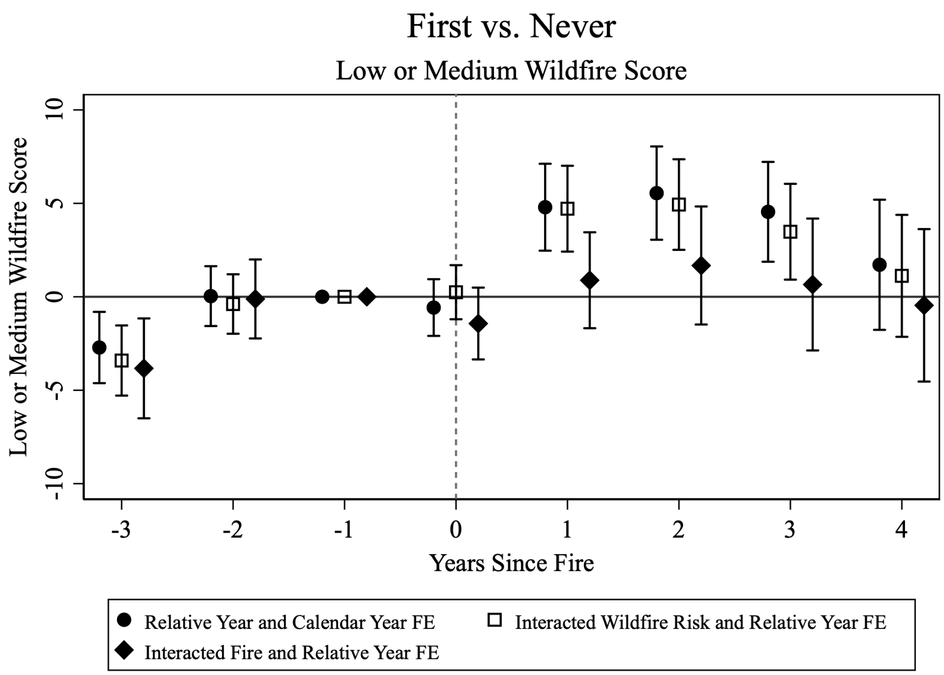
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating different empirical specifications in the UCCCP data from 2014 to 2021. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). There is an increase in the likelihood of moving away starting the year after the fire, and this effect persists for four years after the fire across all specifications. The "Relative Year and Calendar FE" plots the coefficients from estimating Equation 1. The "Interacted Wildfire Risk and Relative Year FE" plots the coefficients from estimating Equation 3. The "Interacted Fire and Relative Year FE" plots the coefficients from estimating Equation 4.

Figure A7: Similar Likelihood of Being Low or Medium Wildfire Risk After First Burn Across Control Groups



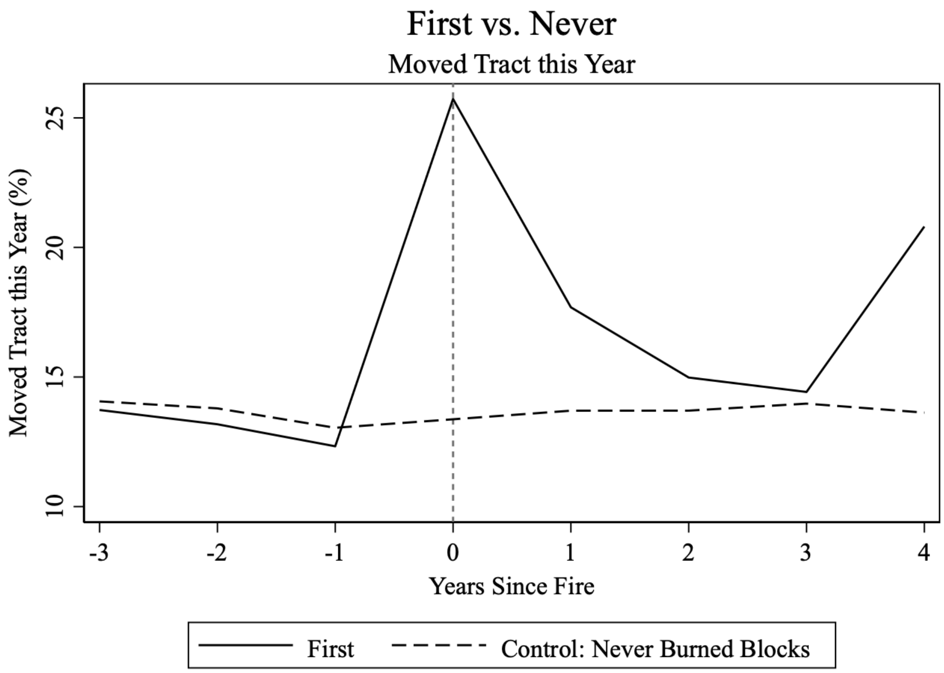
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 and with different control groups. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. My preferred control group is individuals in never-burned blocks, because by definition, the wildfire risk scores are the same for the treated and the control because the wildfire risk is defined at the census tract level. Using the other control groups – people within one mile away and people one to five miles away from the perimeter of the fire – may introduce bias because the wildfire risk scores for the control groups are different from the treated groups: At time 0, the year of the fire that I use to define the treated and the control groups, people in blocks burned for the first time are less likely to be in a safe area. For ease of interpretation, I prefer the never-burned block as the control group, but I present the results for the other control groups for transparency and completeness.

Figure A8: Similar Likelihood of Being in Low or Medium Wildfire Risk After First Burn Across Empirical Specifications



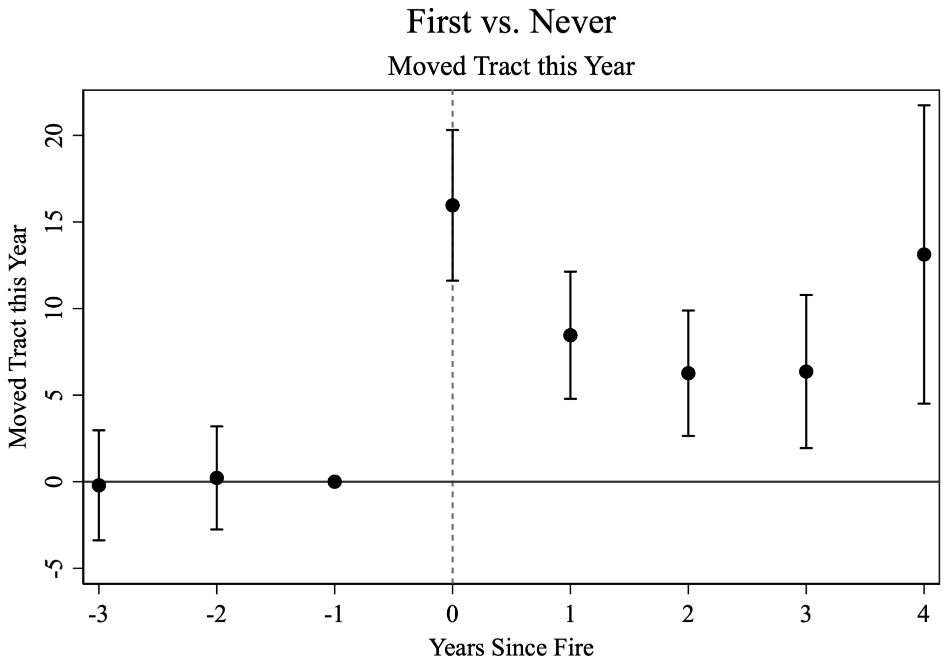
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating different empirical specifications in the UCCCP data from 2014 to 2021. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. There is an initial increase in the likelihood of moving to a safe area, though this falls over time. The "Relative Year and Calendar FE" plots the coefficients from estimating Equation 1. The "Interacted Wildfire Risk and Relative Year FE" plots the coefficients from estimating Equation 3. The "Interacted Fire and Relative Year FE" plots the coefficients from estimating Equation 4.

Figure A9: Average Likelihood of Annual Migration Rates of Treated vs. Control Before First Fire



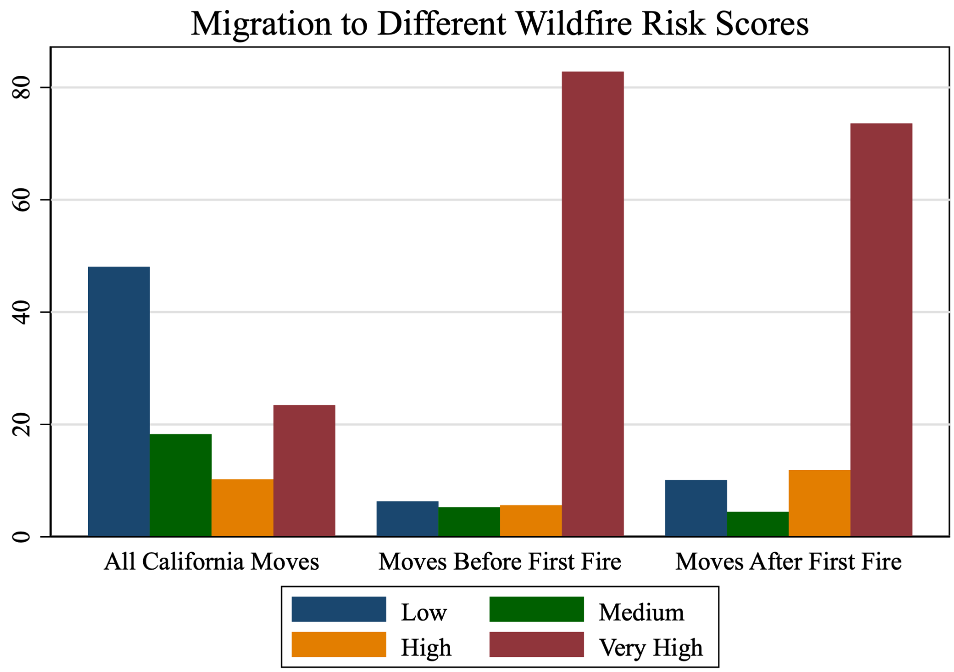
Notes: This graph shows the percentage of individuals who moved tracts within a given relative year from the fire ("Moved Tract This Year") for the treated and control groups in the UCCCP data. The treated group consists of individuals living in census blocks that are burned for the first time. The control group consists of people living within the same census tract as the first-burned blocks but in blocks that are never burned. The time is standardized to be relative to the year of the first fire that impacted the block. Before the fire (i.e., time 0), the migration rates are the same and parallel, giving credibility to this empirical strategy. The increase in the likelihood of moving within a given year persists even years after the wildfire, suggests that individuals experience housing instability after the event.

Figure A10: Sustained Increased Likelihood of Annual Migration Rates in a Given Year After First Fire



Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data moved tracts within a given year ("Moved Tract this Year"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving within a given year starting the year of the fire, and this effect persists for four years after the fire.

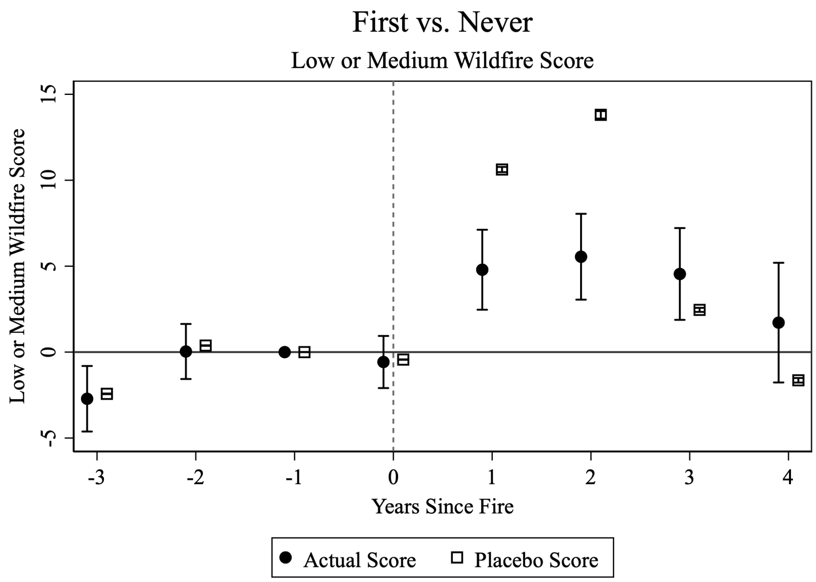
Figure A11: Migration to Different Wildfire Risk Scores



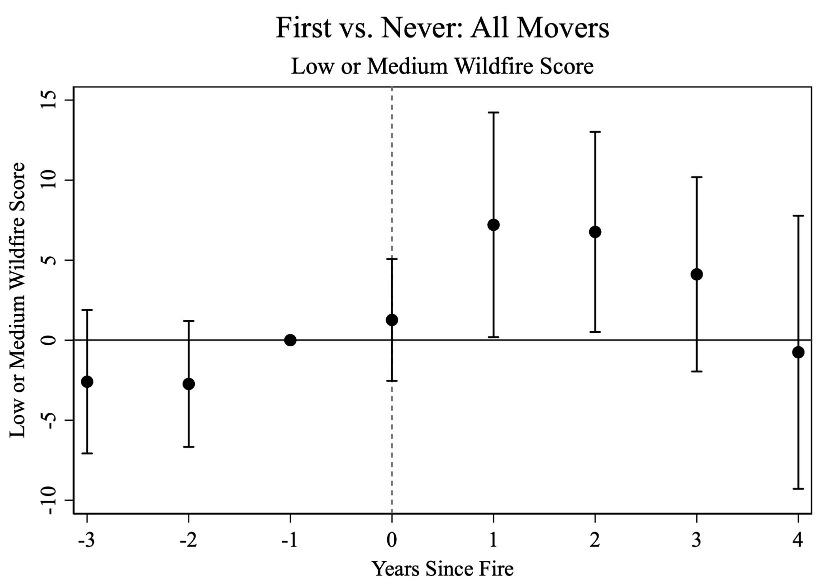
Notes: This graph shows the wildfire risk score distribution for people who moved in three different populations. “All California Moves” is the population of all movers within California from 2014 to 2021 in the UCCCP data. “Movers Before First Fire” is the population of individuals who lived in a block that is burned for the first time but who moved before the fire. “Movers After First Fire” is the population of individuals who lived in a block that is burned for the first time but who moved after the fire. Although there is an increase in the percentage of people who go to low- or medium-wildfire-risk areas, it is a far smaller proportion than would be expected from the overall California mover population. This suggests that people who live in high-risk areas may be selected in some way since their choice of wildfire risk is not similar to that of California movers overall.

Figure A12: Counterfactual Moves

(a) Random Moves by California Movers

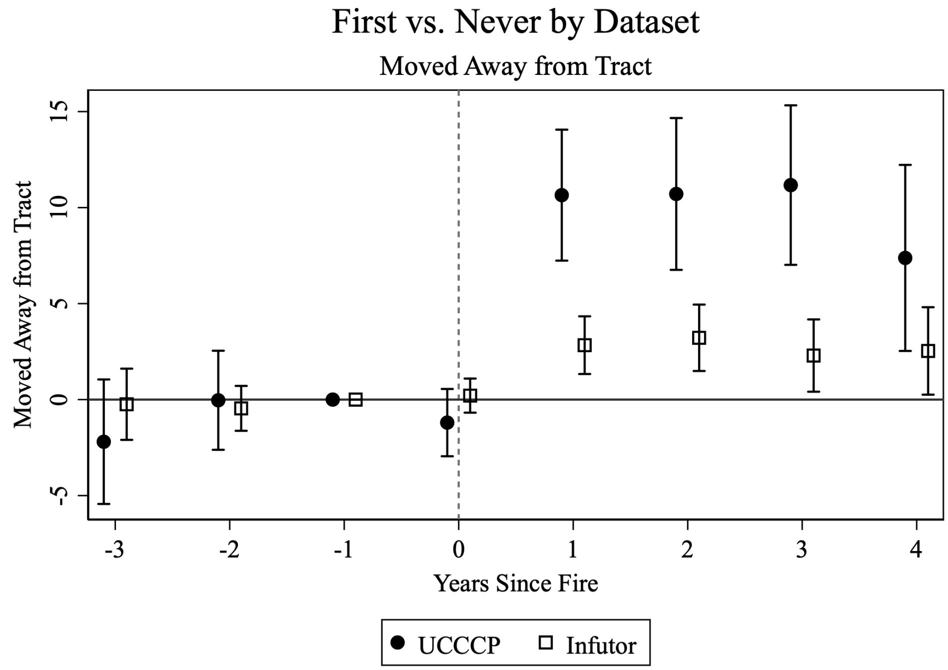


(b) Movers from Never-Burned Blocks



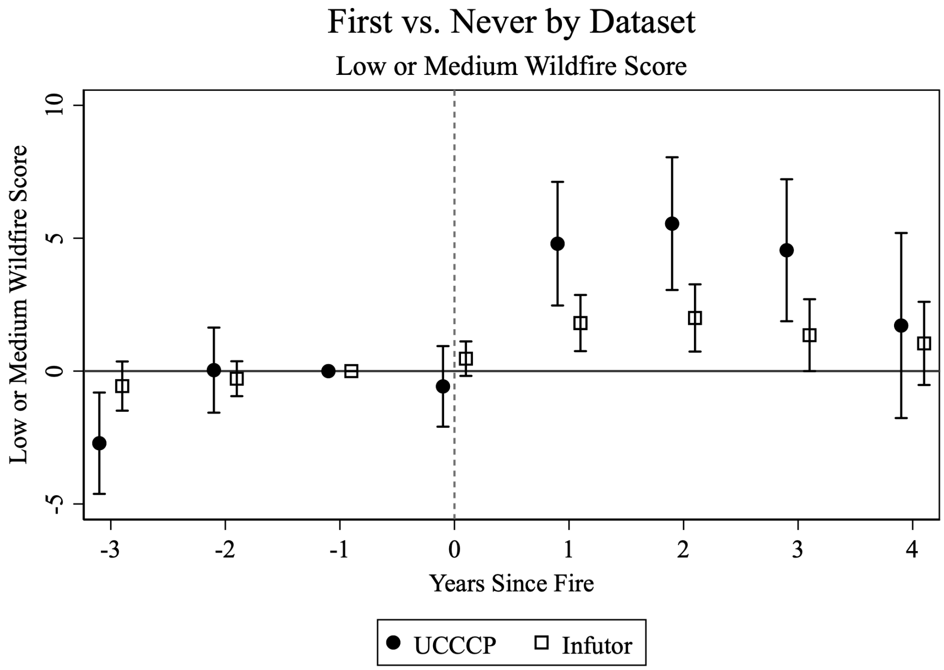
Notes: These graphs show the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two alternative control groups. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. There are minimal differential likelihoods of an individual being in a safe tract before the fire, lending credibility to this empirical strategy. In Figure A12(a), "Actual Score" shows the regression coefficients from taking the actual location decisions seen in the data, whereas "Placebo Score" shows the regression coefficients from replacing the location decisions of the treated after the wildfire with those of a random mover in California. These results show that though there is some evidence of adaptive migration in the first two years, it is lower than would be expected for the average Californian mover. The location choices are similar between people from burned blocks and the average mover after four years. Figure A12(b) plots the regression coefficients for the population of individuals who moved the year of the fire. It shows that those in the area burned for the first time who moved are initially more likely to move to safe areas than are people who moved in the never-burned blocks that year, though there are no differences in the longer term.

Figure A13: Though UCCCP has higher migration rates, the migration results across UCCCP and Infutor follow a similar pattern.



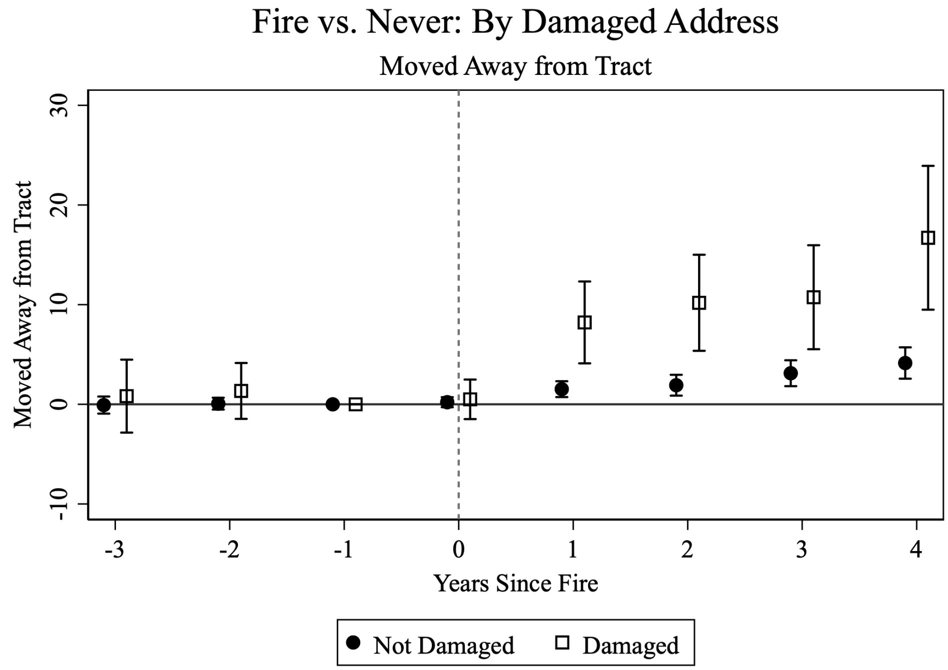
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 from 2014 to 2021 in two datasets. The first dataset is the University of California Consumer Credit Panel (UCCCP), and the second dataset is Infutor. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy across these datasets. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect persists for four years after the fire for both datasets.

Figure A14: The likelihood of being in a safe tract across UCCCP and Infutor follows a similar pattern.



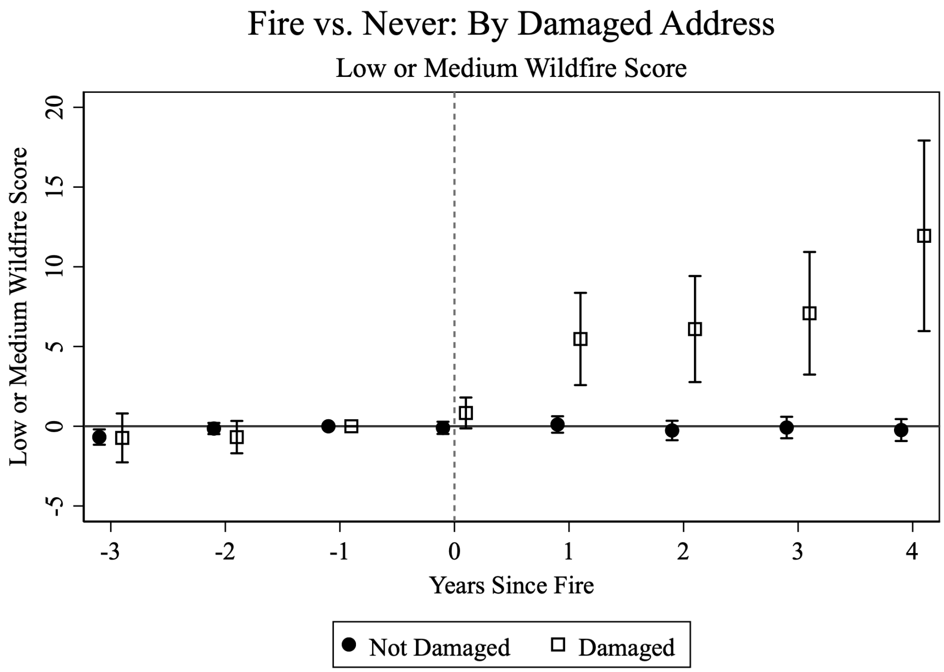
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 from 2014 to 2021 in two datasets. The first dataset is the University of California Consumer Credit Panel (UCCCP), and the second dataset is Infutor. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of being in a safe tract after the fire, though the effect dissipates four years after the fire for both datasets.

Figure A15: Both those in damaged and not damaged addresses are more likely to move after the fire.



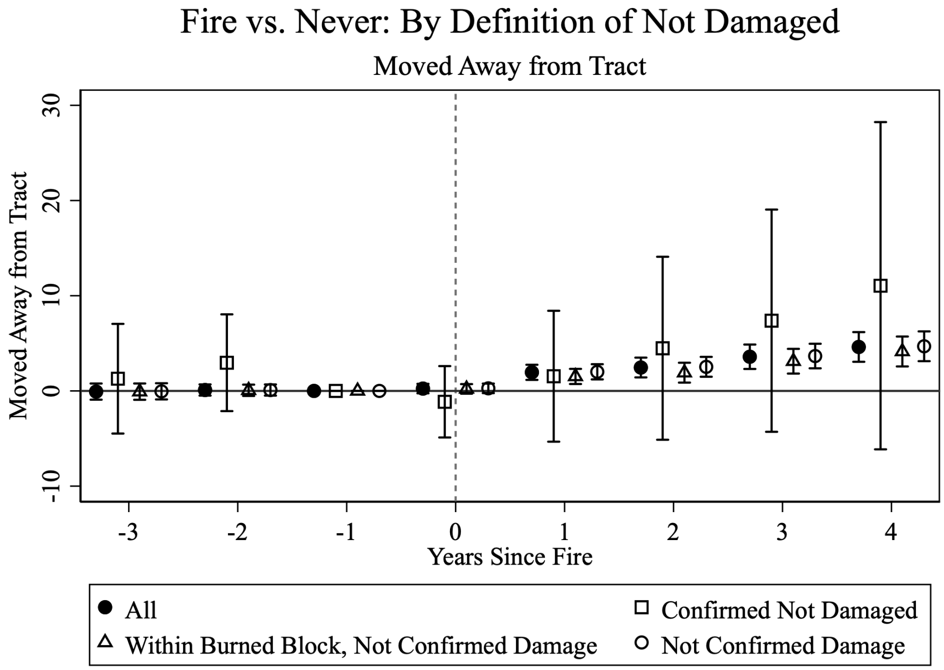
Notes: This graph shows the coefficients for the relative time indicator variables and the fire interaction terms from estimating Equation 1 in the Infutor and the Cal Fire Damage Inspection (DINS) data from 2013 to 2021 across two different treatment groups. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The "Not Damaged" coefficients are for people who live in a census block that is burned but whose homes are not identified as damaged from the DINS data. The "Damaged" coefficients are for people whose homes are identified as damaged from the DINS data. There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving away starting the year after the fire across both groups, though understandably the coefficients are higher for those whose homes are damaged.

Figure A16: Only those in damaged addresses are more likely to move to safe areas after the fire.



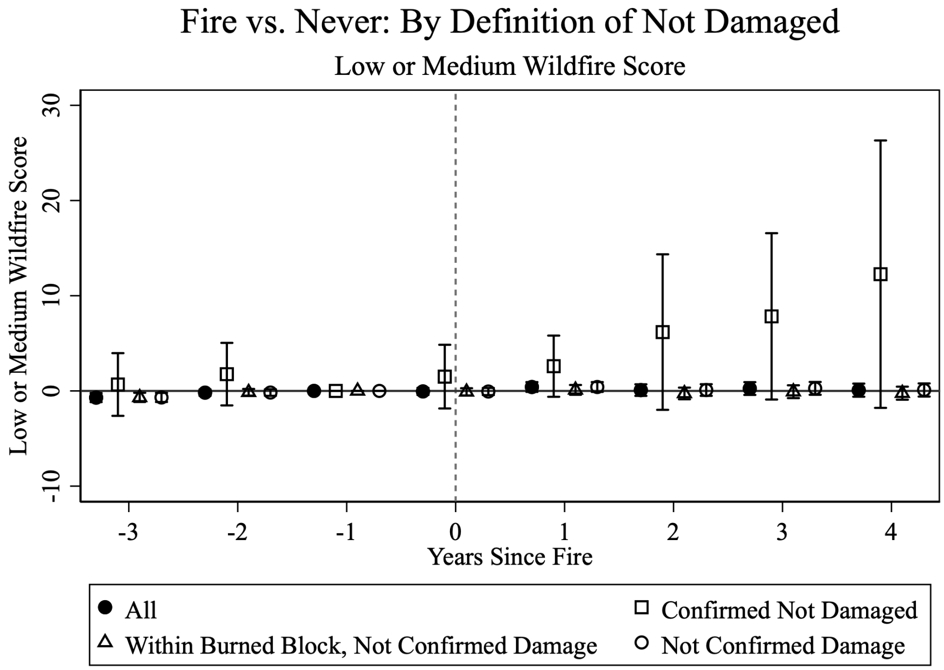
Notes: This graph shows the coefficients for the relative time indicator variables and the fire interaction terms from estimating Equation 1 in the Infutor and the Cal Fire Damage Inspection (DINS) data from 2013 to 2021 across two different treatment groups. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The "Not Damaged" coefficients are for people who live in a census block that is burned but whose homes are not identified as damaged from the DINS data. The "Damaged" coefficients are for people whose homes are identified as damaged from the DINS data. There are no differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe area starting the year after the fire only for those whose homes are damaged, which could be because only those whose homes are damaged receive substantial compensation after the fire.

Figure A17: The increased likelihood of moving away from the tract is similar across the definitions of the not damaged.



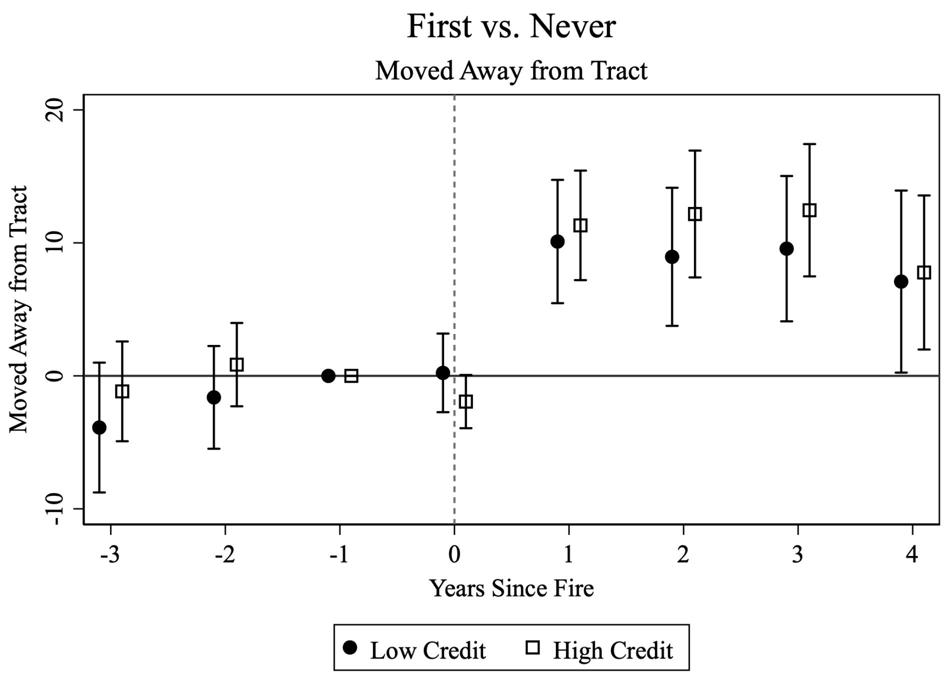
Notes: This graph shows the coefficients for the relative time indicator variables and the fire interaction terms from estimating Equation 1 in the Infutor and the Cal Fire Damage Inspection (DINS) data from 2013 to 2021 across three different definitions of "Not Damaged." The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The "All" coefficients are for everyone who lived in a census block that is burned. The "Confirmed Not Damaged" coefficients are for people who live in a home that is confirmed to have no damage from the DINS data. Because this is a rare classification that they began to incorporate after 2018, the standard errors for this are likely large because of low power. The "Within Burned Block, Not Confirmed Damage" – the main definition of "Not Damaged" used – is for people who live in a census block that is burned for the first time but whose homes are not identified as damaged from the DINS data. The "Not Confirmed Damage" coefficients are for people whose homes are not in the DINS data. There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. The trends are qualitatively similar across these different definitions of "Not Confirmed."

Figure A18: There is a null effect on the likelihood of moving to a low or medium wildfire risk area across the definitions of the not damaged.



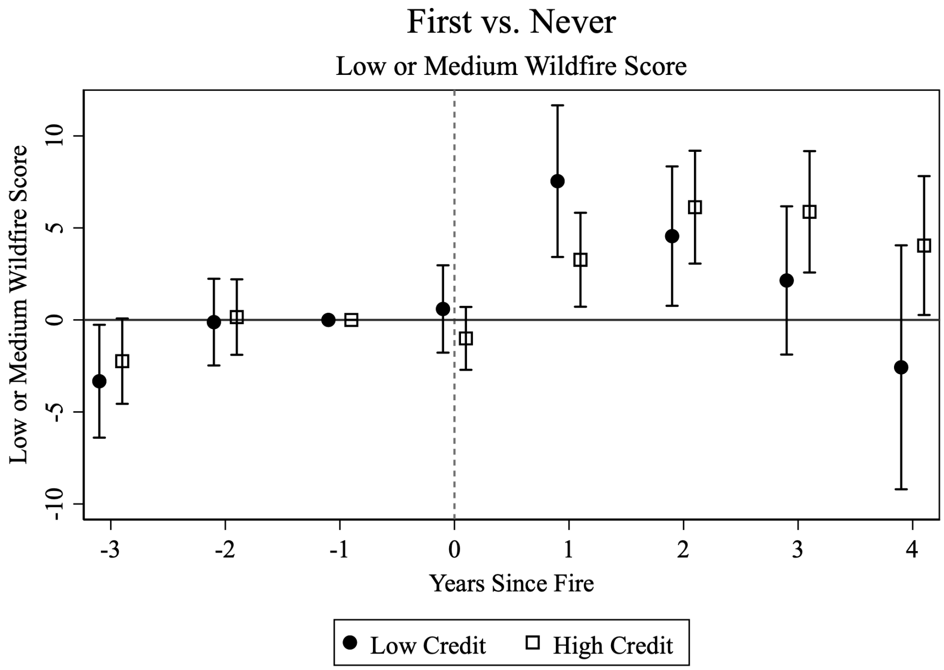
Notes: This graph shows the coefficients for the relative time indicator variables and the fire interaction terms from estimating Equation 1 in the Infutor and the Cal Fire Damage Inspection (DINS) data from 2013 to 2021 across three different definitions of "Not Damaged." The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The "All" coefficients are for everyone who lived in a census block that is burned. The "Confirmed Not Damaged" coefficients are for people who live in a home that is confirmed to have no damage from the DINS data. Because this is a rare classification that they began to incorporate after 2018, the standard errors for this are likely large because of low power. The "Within Burned Block, Not Confirmed Damage" – the main definition of "Not Damaged" used – is for people who live in a census block that is burned for the first time but whose homes are not identified as damaged from the DINS data. The "Not Confirmed Damage" coefficients are for people whose homes are not in the DINS data. There are no differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. The trends are qualitatively similar across these different definitions of "Not Confirmed." The increase in adaptive migration for those that are confirmed to not have damage is not statistically significant, though it could reflect that those who were motivated enough to request a inspection – even though they did not have any damage – could be more likely to want to move away from wildfire risk.

Figure A19: Both people with low and high credit scores are more likely to move and stay away after four years.



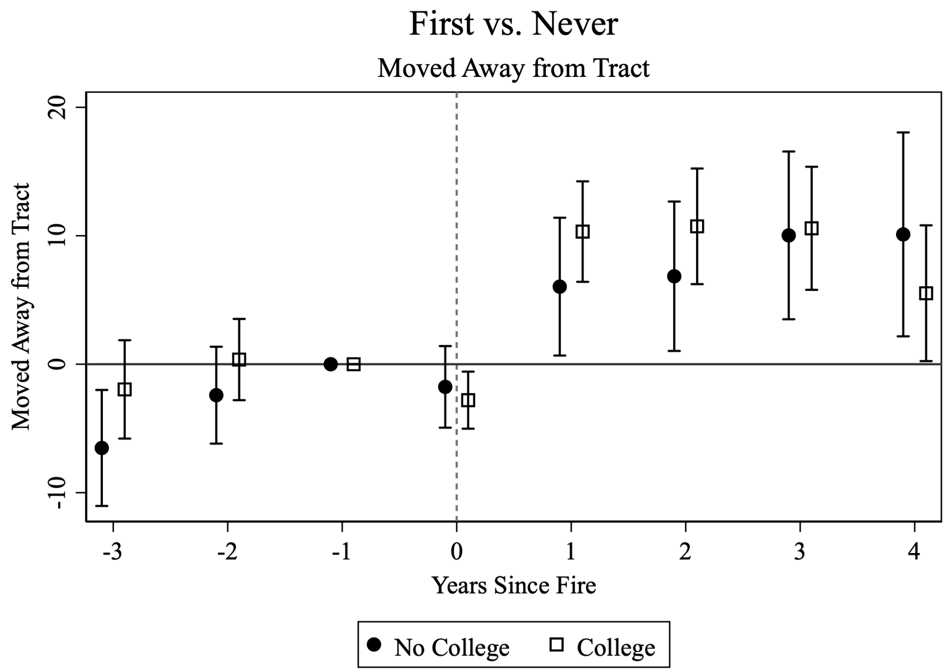
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals one if the individual is at a different tract than where they were the year before the first fire ("Moved Away from Tract"). The populations are defined as people who have high credit scores the year before the fire ($\geq$ 700) and people who have low credit scores ($<$ 700). There are no statistically significant differences in migration rates before the fire for these groups, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect persists four years after the fire for both credit groups.

Figure A20: Both people with low and high credit scores are initially more likely to move to a safe area, though only the high credit are more likely to be in a safe area after four years.



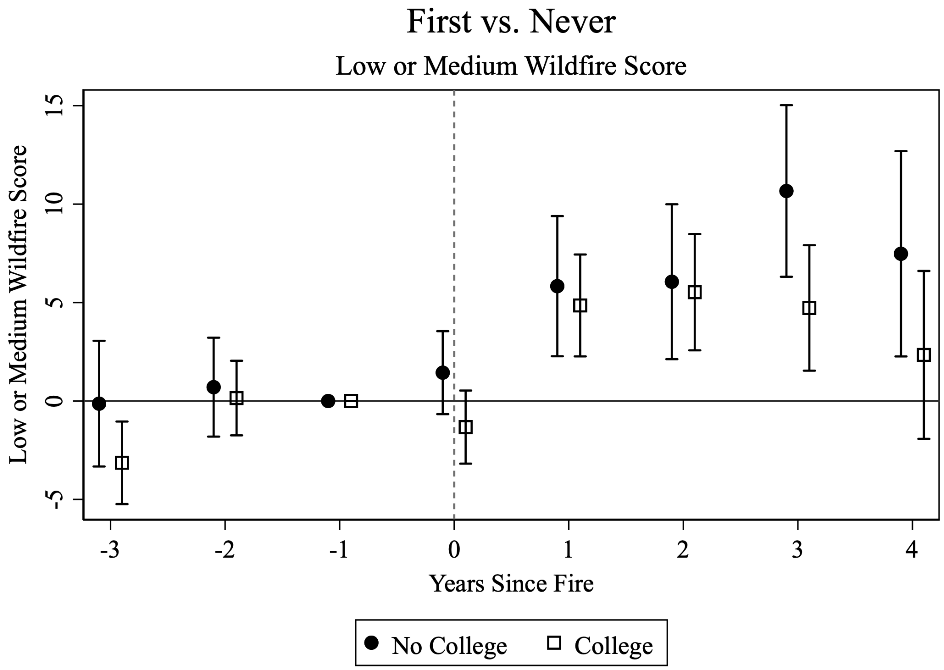
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The populations are defined as people who have high credit scores the year before the fire ($\geq$ 700) and people who have low credit scores ($<$ 700). There are no differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe place starting the year after the fire. This increase persists only for people with high credit scores, who are statistically significantly more likely to be in a safe area four years after the fire. The coefficient for people with high credit scores is also statistically significantly different from the coefficient for people with low credit scores.

Figure A21: Both people with and without college education are more likely to move and stay away after four years.



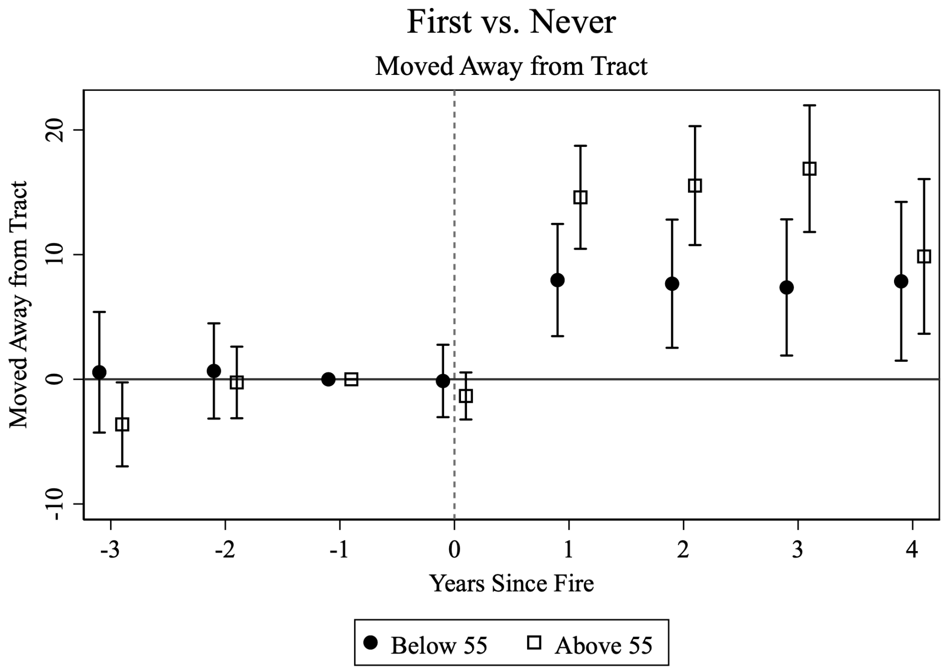
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The populations are defined as people who have a college degree and people without a college degree. There are minimal statistically significant differences in migration rates before the fire for these groups, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect persists for four years after the fire for both education groups.

Figure A22: Both people with and without college education are initially more likely to move to a safe area, though only people without college are more likely to be in a safe area after four years.



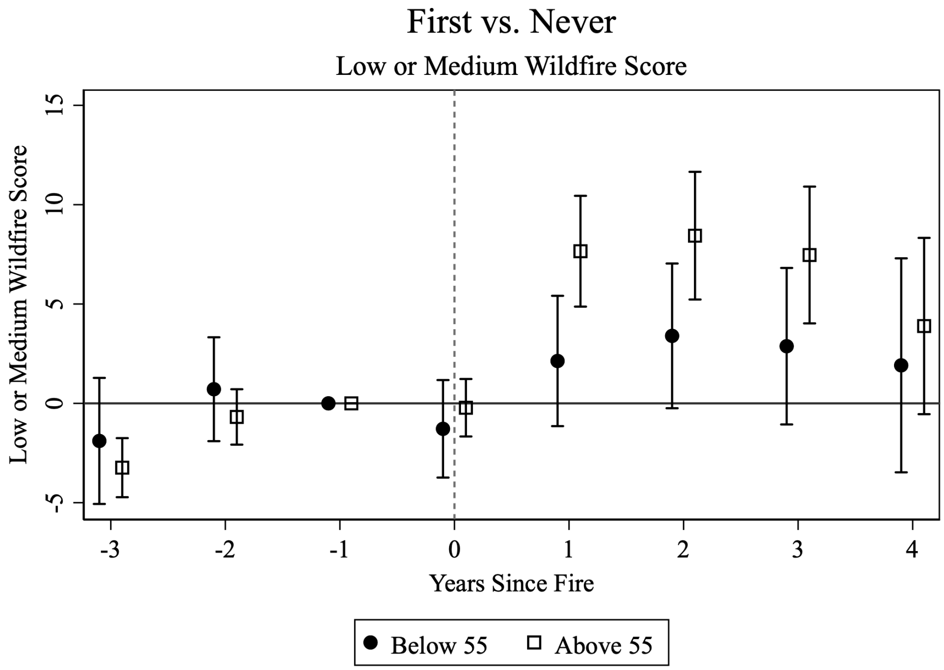
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The populations are defined as people who have a college degree and people without a college degree. There are minimal statistically significant differences in wildfire risk before the fire for these groups, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe place starting the year after the fire. This increase persists only for people without college, who are statistically significantly more likely to be in a safe area. However, the increase for those without college is not statistically significantly different from those with college.

Figure A23: Both age groups are more likely to move away compared to their never-burned counterparts.



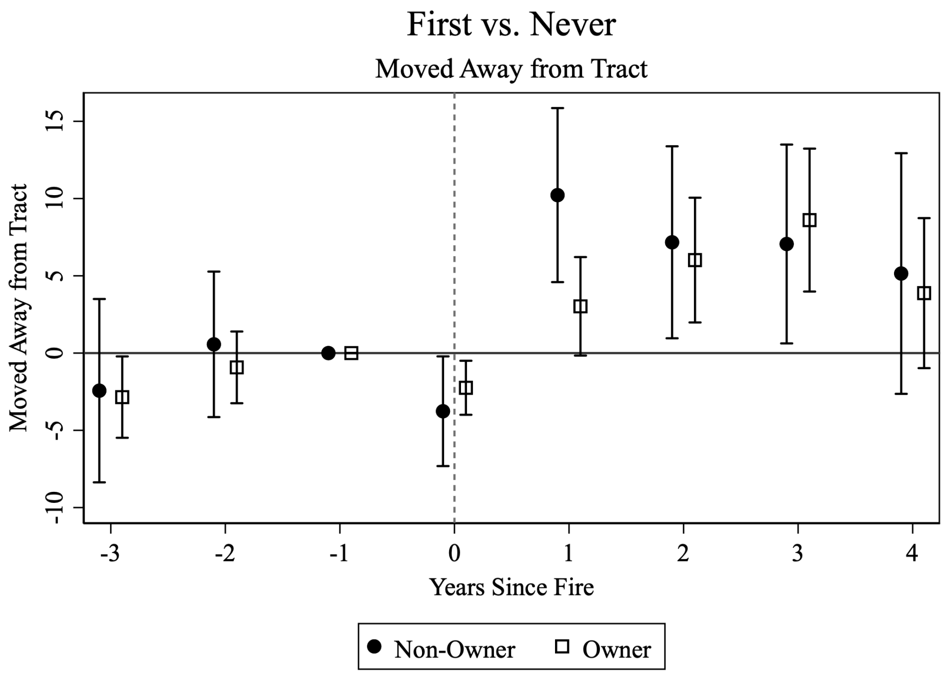
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The populations are defined as people who are below 55 at the time of the fire and people above 55. I choose 55 as the age cut-off because Proposition 19 allows people who are above 55 as well as people whose homes are destroyed by a wildfire to transfer their tax burden to another property in California. There are minimal statistically significant differences in migration rates before the fire for these groups, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect persists four years after the fire for both age groups.

Figure A24: Neither age group is more likely to move to a safe area compared to their never-burned counterparts.



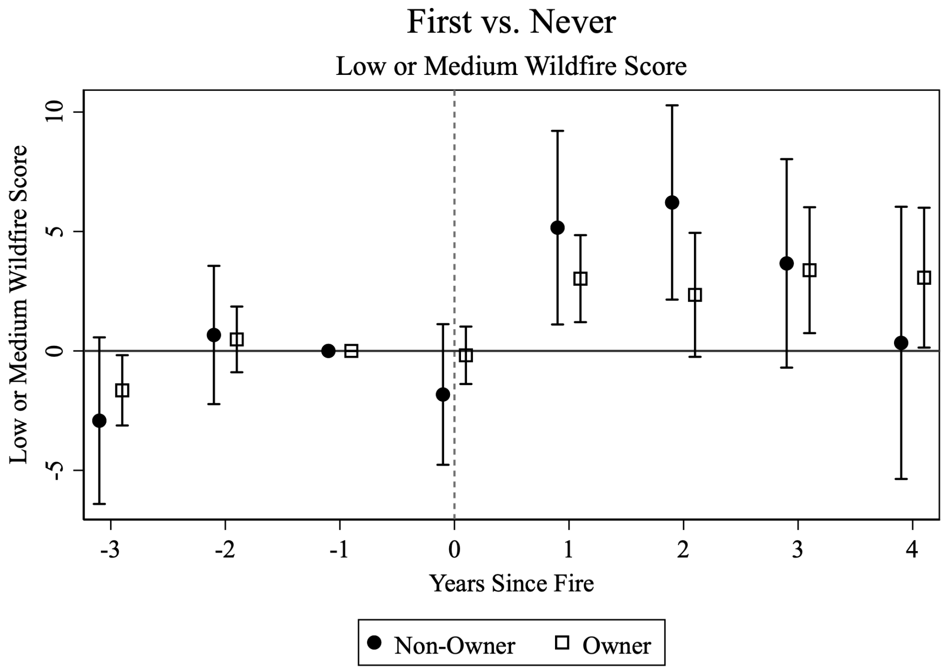
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 (“Low or Medium Wildfire Score”), as defined by FEMA’s wildfire risk index, which ranges from 0 to 100. The populations are defined as people who are below 55 at the time of the fire and people above 55. I choose 55 as the age cut-off because Proposition 19 allows people who are above 55 as well as people whose homes are destroyed by a wildfire to transfer their tax burden to another property in California. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe place starting the year after the fire for people above 55. Neither group is more likely to be in a safe area compared to their control groups four years after the fire.

Figure A25: Both people who are identified as owners and non-owners are more likely to move away, though they are not statistically significantly different from their counterparts in the never-burned blocks.



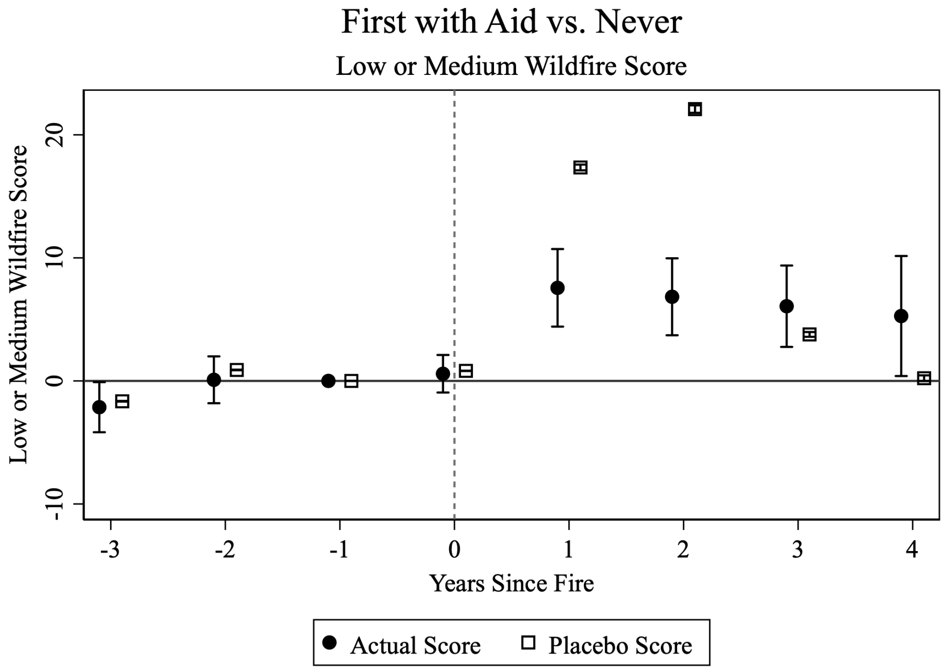
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The populations are defined as people who are identified as a homeowner and people who are not. There are minimal statistically significant differences in migration rates before the fire for these groups, lending credibility to this empirical strategy. There is an increase in the likelihood of moving away starting the year after the fire. Neither group is more likely to move away compared to their control groups four years after the fire.

Figure A26: Only people who are identified as owners are more likely to be in a safe area after four years.



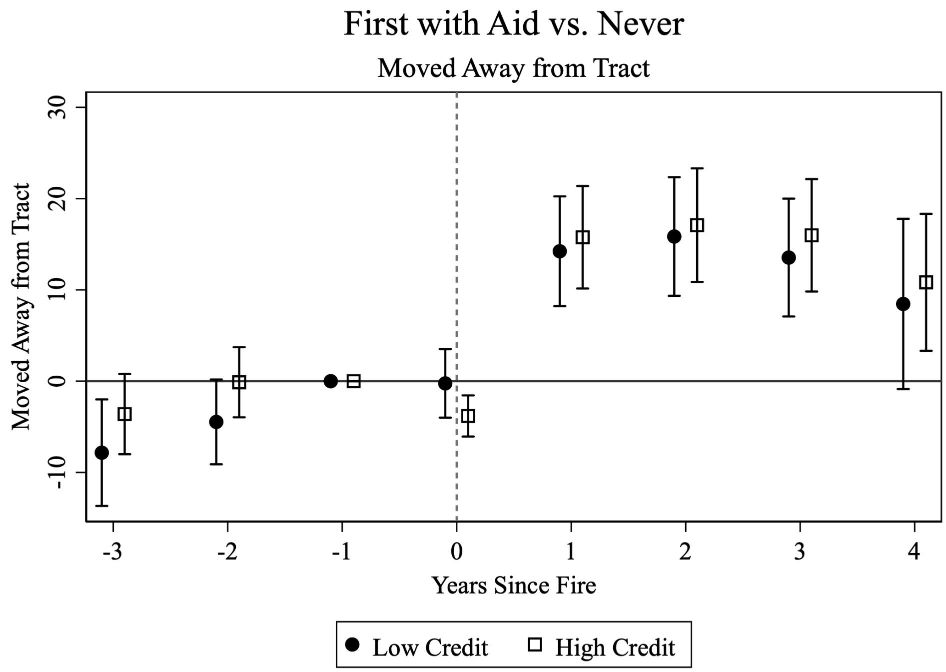
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 1 in the UCCCP data from 2014 to 2021 across two populations. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The populations are defined as people who are identified as a homeowner and people who are not. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe place starting the year after the fire. This increase persists only for owners, who are statistically significantly more likely to be in a safe area. However, the increase for owners is not statistically significantly different from people who are not.

Figure A27: Receipt of government aid is associated with increased adaptive migration, though not as much as expected with a random mover.



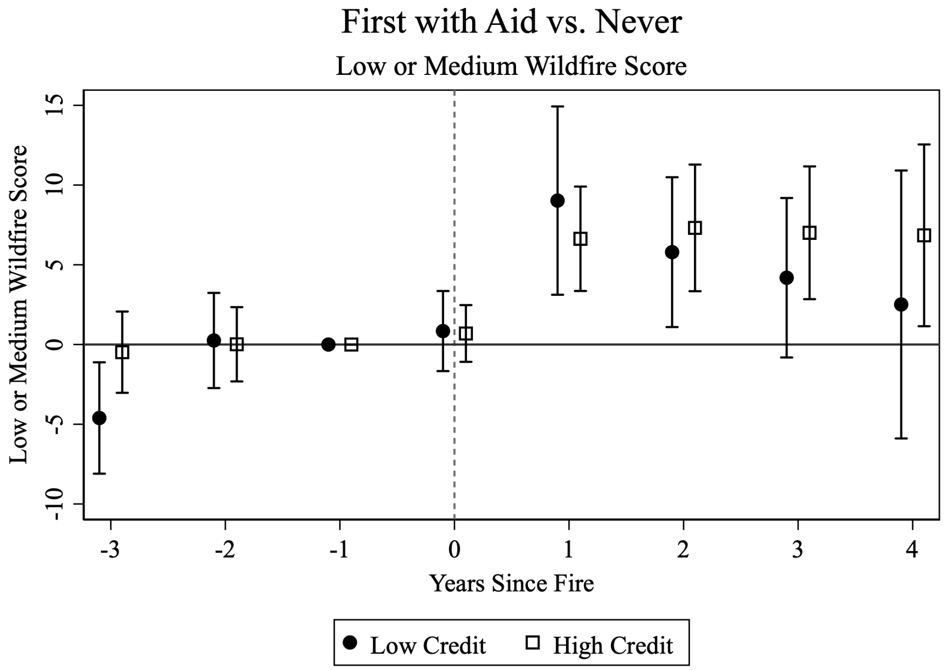
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire with aid interaction terms from estimating Equation 5 in the UCCCP data from 2014 to 2021. The aid is defined as whether any FEMA Individual Households Program assistance is disbursed for the fire. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. "Actual Score" shows the regression coefficients from taking the actual location decisions seen in the data, whereas "Placebo Score" shows the regression coefficients from replacing the location decisions of the treated after the wildfire with those of a random mover in California. These results show that though there is some evidence of adaptive migration in the first two years, it is lower than would be expected for the average Californian mover. People in blocks that experience a first fire for which aid is disbursed are more likely to be in safe areas after four years.

Figure A28: Government aid is associated with increased migration for all credit groups.



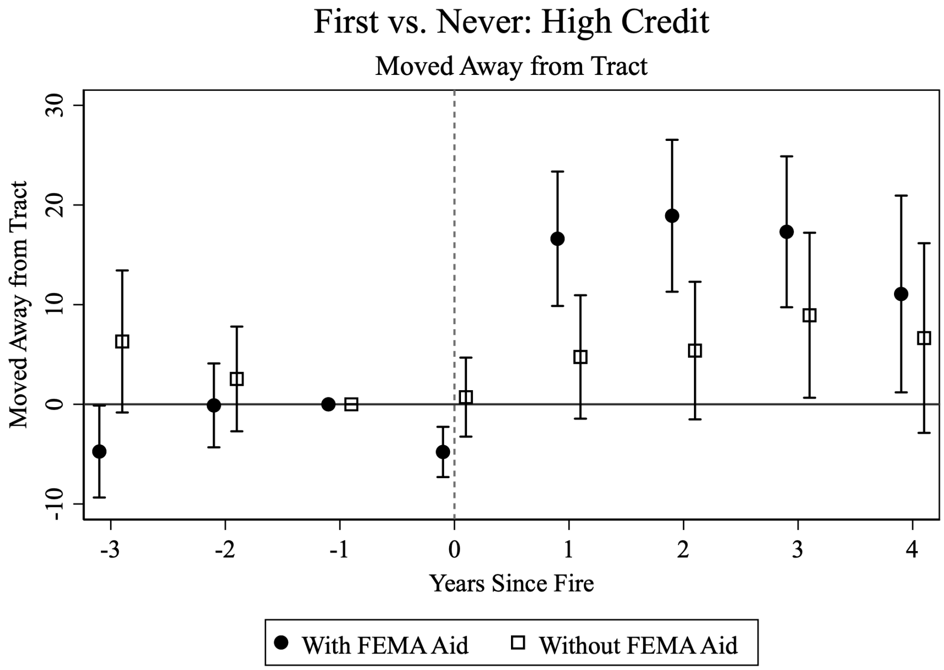
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire with aid interaction terms from estimating Equation 5 in the UCCCP data from 2014 to 2021 across two groups. The aid is defined as whether any FEMA Individual Households Program assistance is disbursed for the fire. The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). The populations are defined as people who have high credit scores the year before the fire (≥ 700) and people who have low credit scores (< 700). There are minimal statistically significant differences in migration rates before the fire for these groups, lending credibility to this empirical strategy. There is a sharp increase in the likelihood of moving away starting the year after the fire, and this effect persists four years after the fire for people with high credit scores. However, the year four coefficient for people with high credit scores and aid is not statistically significantly different from the coefficient for people with low credit scores and aid.

Figure A29: Government aid helps people with low credit scores in the short run and people with high credit scores in the longer run move to safe areas.



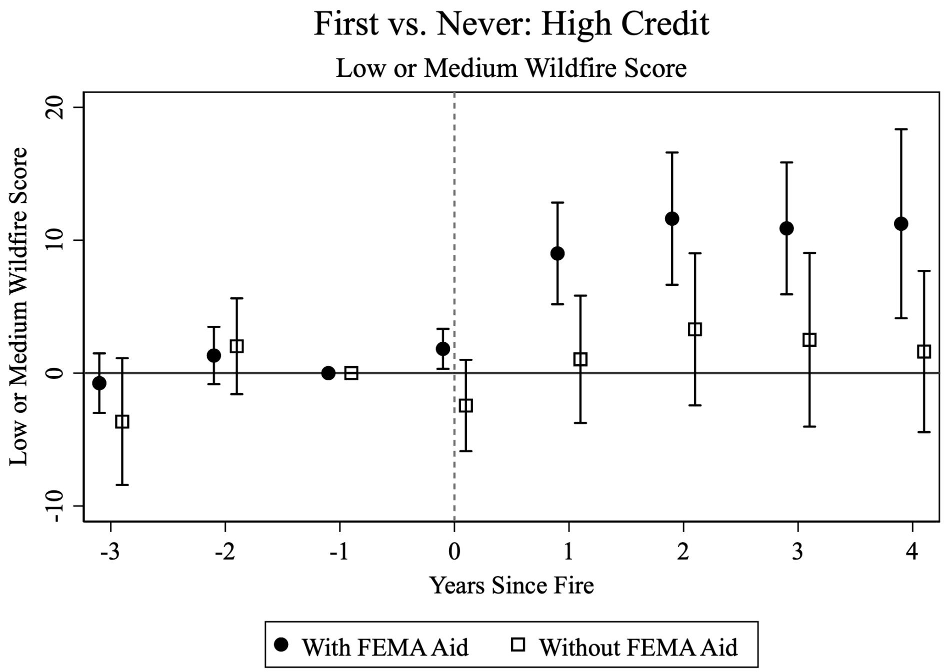
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire with aid interaction terms from estimating Equation 5 in the UCCCP data from 2014 to 2021 across two groups. The aid is defined as whether any FEMA Individual Households Program assistance is disbursed for the fire. The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. The populations are defined as people who have high credit scores the year before the fire (≥ 700) and people who have low credit scores (< 700). There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. There is an increase in the likelihood of moving to a safe place starting the year after the fire. This increase persists only for people with high credit scores, who are statistically significantly more likely to be in a safe area four years after the fire. However, the year four coefficient for people with high credit scores and aid is not statistically significantly different from the coefficient for people with low credit scores and aid.

Figure A30: Government aid is associated with increased migration for people with high credit scores.



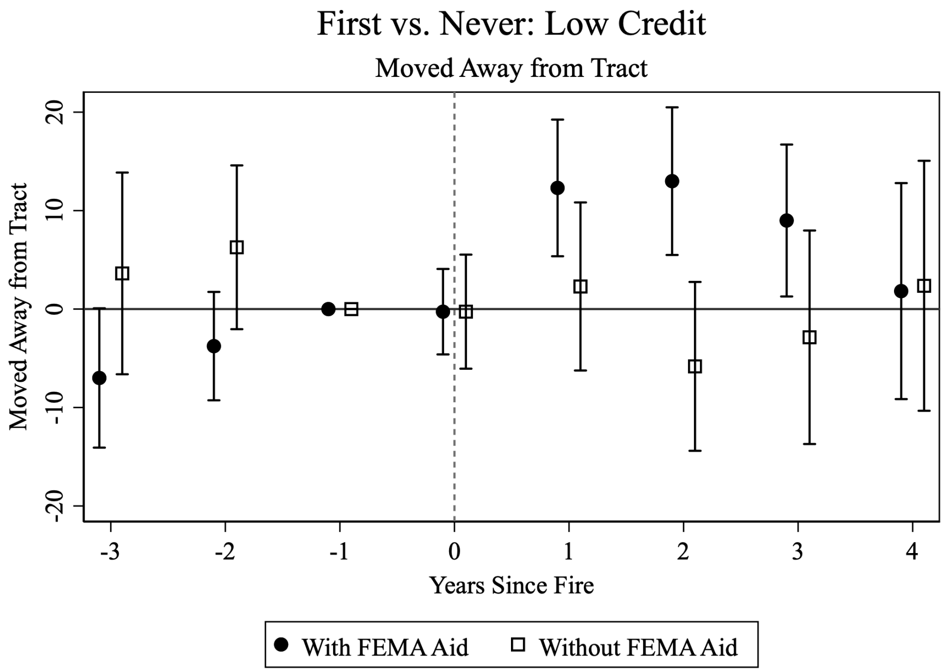
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 5 in the UCCCP data from 2014 to 2021 separately for first fires for which any FEMA Individuals and Households Program aid is disbursed and first fires for which no aid is disbursed for people with high credit scores the year before the fire ($\geq$ 700). The outcome variable is an indicator variable that equals 100 if I observe the individual in the data in a different tract from where she was at the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. People with high credit scores that experience first fires for which aid is disbursed are more likely to move away, whereas those that experience first fires for which aid is not disbursed have lower migration effects.

Figure A31: Government aid is associated with increased likelihood of being in a safe tract for people with high credit scores.



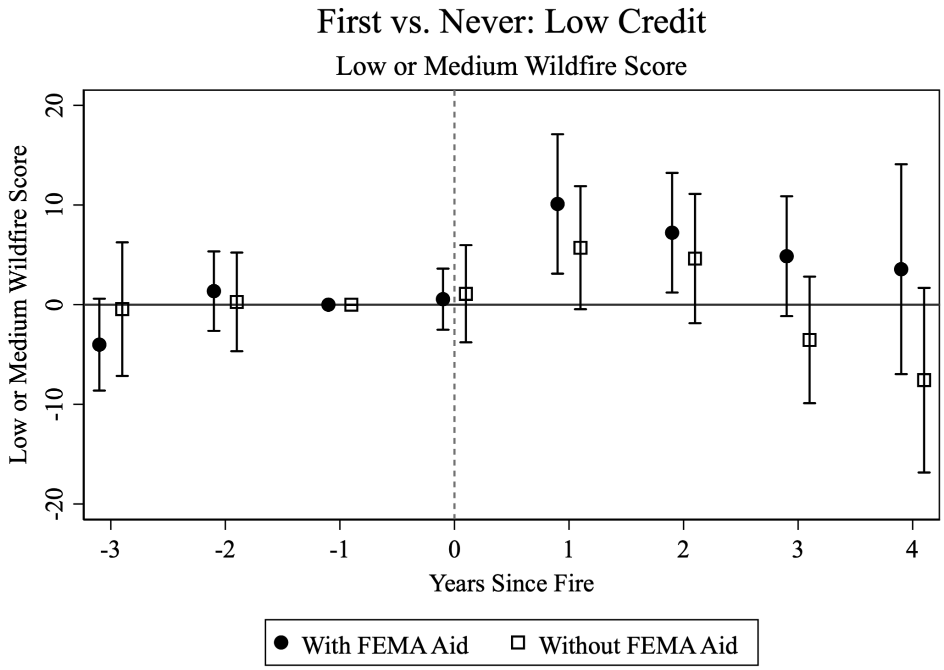
Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 5 in the UCCCP data from 2014 to 2021 separately for first fires for which any FEMA Individuals and Households Program aid is disbursed and first fires for which no aid is disbursed for people with high credit scores the year before the fire ($\geq$ 700). The outcome variable is an indicator variable that equals 100 if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), as defined by FEMA's wildfire risk index, which ranges from 0 to 100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. People with high credit scores that experience first fires for which any aid is disbursed are more likely to be in safe areas, even four years after the fire, whereas those that experience first fires for which no aid is disbursed are not.

Figure A32: Government aid is associated with increased migration for those with low credit.



Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 5 using the UCCCP data from 2014-2021, separately for first fires that receive FEMA Individuals and Households Program aid and first fires that do not, for those with low credit (those whose credit score at the time of the fire is < 700). The outcome variable is an indicator variable that equals one if the individual is at a different tract than where they were the year before the first fire ("Moved Away from Tract"). There are no statistically significant differences in migration rates before the fire, lending credibility to this empirical strategy. Low-credit individuals – regardless of whether they are in a first fire that receives aid or not – are not more likely to move away in the longer-term.

Figure A33: Government aid is associated with increased likelihood of being in a safe tract for those with low credit.



Notes: This graph shows the coefficients for the relative time indicator variables and the first fire interaction terms from estimating Equation 5 using the UCCCP data from 2014-2021, separately for first fires that receive FEMA Individuals and Households Program aid and first fires that do not, for those with low credit (those whose credit score at the time of the fire is < 700). The outcome variable is an indicator variable that equals one if the individual is in a tract that has a wildfire risk score that is below 50 ("Low or Medium Wildfire Score"), which is defined using FEMA's wildfire risk index that ranges from 0-100. There are minimal differential likelihoods of being in a safe tract before the fire, lending credibility to this empirical strategy. Low-credit individuals – regardless of whether they are in a first fire that receives aid or not – are not more likely to be in a safe area in the longer-term, with those without aid having a decrease in the likelihood.

B Appendix Tables

Table B1: Tracts with Higher Wildfire Risk Have Lower House Prices

	United States		California	
FEMA Wildfire Score	-1.550***		-1.088***	
	(0.028)		(0.086)	
FEMA Wildfire Risk Category		-43.171***		-32.219***
		(0.799)		(2.732)
Constant	401.895***	436.583***	599.317***	629.791***
	(1.782)	(2.407)	(4.825)	(6.862)
N	62,468	62,468	7,635	7,635

Notes: This table reports the coefficients from regressing wildfire risk on house prices. The wildfire risk data are from FEMA and list the wildfire risk score at the census tract level. "FEMA Wildfire Score" ranges from 0 to 100. "FEMA Wildfire Risk Category" is 1 if the tract is low wildfire risk (i.e., risk score < 25), 2 if medium wildfire risk (i.e., 25 to 50), 3 if high wildfire risk (i.e., 50 to 75), and 4 if very high wildfire risk (i.e., $>$ 75). The house price data are from the Federal Housing Finance Agency (FHFA) and at the census tract level. The house price index (HPI) is calculated by measuring average price changes in repeat sales on the same set of properties. A higher HPI corresponds to more expensive properties. The data used in this regression are for the year 2021. The coefficients reflect that areas with higher wildfire risk have lower house prices, for both the United States overall and California alone.

Table B2: Movers vs. Non-Movers Summary Statistics

	Moved		Did Not Move			
	Mean	SD	Mean	SD	Difference	p-value
Demographic Characteristics						
Age	51.39	(18.67)	52.83	(18.02)	-1.44	0.29
Male	0.53	(0.50)	0.49	(0.50)	0.03	0.37
Married	0.59	(0.49)	0.63	(0.48)	-0.05	0.19
College	0.65	(0.48)	0.70	(0.46)	-0.05	0.14
Financial Characteristics						
Credit Score	687.72	(131.97)	708.42	(111.10)	-20.70	0.02
Number of Open Credit Cards	2.81	(3.13)	2.35	(2.79)	0.46	0.04
Total Credit Limit	19,014.30	(20,603.89)	22,233.68	(24,915.54)	-3,219.37	0.09
Total Payment	919.52	(1,177.67)	1,492.68	(2,615.52)	-573.16	0.00
Number of Open Loans	5.12	(4.71)	4.39	(4.32)	0.73	0.03
Number of Open Auto Loans	0.38	(0.66)	0.30	(0.57)	0.08	0.10
Has Mortgage Loans	0.26	(0.44)	0.32	(0.47)	-0.06	0.05
Bankruptcy	5.34	(22.53)	4.37	(20.45)	0.98	0.54
Number of Current Delinquencies	0.10	(0.37)	0.07	(0.38)	0.03	0.31

Notes: This table reports summary statistics for individuals that I observe in the UCCCP data who moved to a different tract the year of the fire with individuals who did not for the population of people who lived in a census block that burned for the first time. All characteristics are measured the year before the fire occurred.

Table B3: Return Movers vs. Non-Return Movers Summary Statistics

	Returned		Did Not Return			
	Mean	SD	Mean	SD	Difference	p-value
Demographic Characteristics						
Age	51.44	(15.95)	50.88	(17.86)	0.57	0.90
Male	0.63	(0.50)	0.61	(0.49)	0.02	0.89
Married	0.72	(0.46)	0.64	(0.48)	0.09	0.49
College	0.56	(0.51)	0.65	(0.48)	-0.10	0.48
Financial Characteristics						
Credit Score	712.33	(102.38)	733.41	(72.38)	-21.08	0.42
Number of Open Credit Cards	3.78	(4.92)	2.98	(3.12)	0.79	0.52
Total Credit Limit	30,945.83	(38,793.25)	23,198.04	(26,819.52)	7,747.80	0.52
Total Payment	1,763.71	(1,695.61)	1,320.39	(1,800.64)	443.33	0.39
Number of Open Loans	6.22	(6.09)	5.42	(4.98)	0.80	0.61
Number of Open Auto Loans	0.28	(0.46)	0.27	(0.54)	0.01	0.97
Has Mortgage Loans	0.39	(0.50)	0.27	(0.45)	0.12	0.38
Bankruptcy	0.00	(0.00)	6.06	(24.04)	-6.06	0.04
Number of Current Delinquencies	0.00	(0.00)	0.05	(0.21)	-0.05	0.08

Notes: This table reports summary statistics for individuals that I observe in the UCCCP data who returned within four years after the fire with individuals who did not return for the population of people who lived in a census block that burned for the first time and who moved the year of the fire. All characteristics are measured four years after the fire occurred.

Table B4: Characteristics Associated with Migration for Individuals in First- and Never-Burned Blocks

Variable	Coefficient	Standard Error
Age	-0.161***	(0.018)
College	0.410	(0.556)
Married	0.025	(0.508)
Male	-0.055	(0.403)
Duration	-1.497***	(0.180)
Wildfire Risk Score	-0.199***	(0.030)
Overall Risk Score	0.416**	(0.192)
Social Vulnerability Score	-0.067	(0.044)
Expected Annual Loss Score	-0.462**	(0.195)
Number of Insurance Providers	-0.121***	(0.038)
Percent FAIR Policies	0.808**	(0.336)
Credit Score	-0.025***	(0.004)
Number of Open Credit Cards	-0.893***	(0.186)
Total Credit Limit	-0.000	(0.000)
Total Payment	-0.000	(0.000)
Number of Open Loans	0.702***	(0.138)
Number of Open Auto Loans	0.443	(0.401)
Has Mortgage Loans	-5.486***	(0.571)
Bankruptcy	-0.005	(0.010)
Number of Current Delinquencies	-1.430**	(0.651)
Constant	70.956***	(5.525)
R^2	0.089	
N	83048	
Mean	14.05	

Notes: This table reports the coefficients from regressing the listed characteristics on whether the individual moved. The population included in the regression are people living in census blocks that burned for the first time or people living within the same census tract as the first-burned blocks but in blocks that are never burned. These individual-level characteristics are taken from the year before the wildfire burned. The coefficients reflect whether the characteristic is positively or negatively associated with the likelihood of moving. These regression coefficients are used to predict the expected migration rates in Table B5. The data used in estimating this is from the University of California Consumer Credi Panel (UCCCP).

Table B5: Predicted Migration Rates for Individuals in First-Burn vs. Control Blocks

	Treated		Control			
	Mean	SD	Mean	SD	Difference	p-value
Control Groups						
Never	11.817	(9.649)	13.169	(10.072)	-1.352	0.000
One Mile Away	11.388	(7.401)	12.978	(7.883)	-1.590	0.000
One to Five Miles Away	12.667	(6.735)	13.550	(6.942)	-0.882	0.000

Notes: This table reports the predicted migration rates from estimating regressions of characteristics on whether the individual moved, as seen in Table B4. This regression and prediction exercise is done for three different control groups: blocks that are never burned but within a census tract that has a block that is burned for the first time, blocks within the one mile perimeter of the fire that burns a block for the first time, and blocks within a one- to five-mile perimeter of that fire. The data used in estimating this is from the University of California Consumer Credi Panel (UCCCP). The predicted migration rates show that the burned areas have lower predicted migration rates compared to the various control groups.

Table B6: First Stage: Politically Competitiveness ($5 - 15\%$) 2014-2021

	Post × Treated × Political Competitiveness (%)			
	$< 5\%$	$< 7\%$	$< 10\%$	$< 15\%$
Post × Treated × IHP	0.329***	0.287***	0.115	0.072
	(0.076)	(0.098)	(0.123)	(0.129)
Post × Treated	0.610***	0.612***	0.637***	0.651***
	(0.068)	(0.069)	(0.075)	(0.078)
R-squared	0.616	0.619	0.629	0.633
N	288,299	288,299	288,299	288,299
Mean	0.228	0.228	0.228	0.228
F-stat	58.02	29.65	14.54	14.83
Controls	Yes	Yes	Yes	Yes
Relative Time FE	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

Notes: I instrument receipt of any FEMA Individuals and Households Program (IHP) aid by political competitiveness. I define a politically competitive county as one in which the difference in the vote share between the top two candidates in the most recent presidential election ranges from "$< 5\%$" to "$< 15\%$." I use shares of "$< 5\%$" for my main definition of political competitiveness. I use data from MIT Election Labs to define the vote shares. I estimate Equation 7 using UCCCP data from 2014 to 2021. I include the average size of the fires within the county (in thousands of acres), the age category of the individual, whether she is married, whether she has a college education, and the duration of time she lives in the census block as controls. I also include relative year, calendar year, and individual fixed effects. I cluster the regression at the county level. The instrument is robust to my defining political competitiveness with vote margins at various thresholds, where the likelihood of aid receipt monotonically decreases as political competitiveness decreases, lending additional credibility to the instrument's relevance.

Table B7: Exclusion Restriction: Politically Competitive Counties and Climate Attitudes

	Fire		< 5%		Fire x < 5%	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Global Warming is Happening	-3.517	0.000	-3.705	0.029	2.548	0.088
Global Warming Will Harm US Within 10 Years	-6.464	0.000	-3.618	0.035	2.097	0.296
Worried About Global Warming	-3.849	0.000	-2.901	0.010	1.883	0.109
Global Warming Will Personally Harm Me	-2.483	0.000	-3.322	0.003	1.095	0.251
Global Warming Will Start to Harm US Citizens	-3.748	0.000	-3.061	0.009	1.376	0.309
Scientists Agree Global Warming is Happening	-5.769	0.000	-4.320	0.051	2.739	0.226
Support Requiring Renewable Sources for Utilities	-1.859	0.001	-1.409	0.074	2.083	0.006
Support Funding Renewable Energy Research	-2.831	0.000	-1.206	0.390	0.997	0.442

Notes: The exclusion restriction requires that a county's political competitiveness impact migration through only aid receipt, nothing else. Although this condition is not directly testable, I evaluate the likelihood of there being different climate attitudes as a way of assessing the validity of the exclusion restriction. I define a politically competitive county as one in which the difference in the vote share between the top two candidates in the most recent presidential election is within 5%. I use data from MIT Election Labs to define vote shares. I estimate Equation 8 using a variety of county-level climate attitudes from the Yale Program on Climate Change Communication. The climate attitudes data are the percentage of people within the county that are estimated to believe in the following statements related to climate change and global warming asked between 2014 and 2021. I find that there are no statistically significantly differential climate attitudes for politically competitive counties that experience a fire.

Table B8: DID IV Results: Political Competitiveness ($< 5\%$) with County Controls

	DID IV		DID IV with County Controls	
	Moved Away from Tract	Low or Medium Wildfire Risk Tract	Moved Away from Tract	Low or Medium Wildfire Risk Tract
Post × Treated × IHP	35.170***	-0.540	45.438***	-3.952
	(8.762)	(8.923)	(11.161)	(10.933)
Post × Treated	-14.195**	4.577	-2.408	2.849
	(7.928)	(4.686)	(10.933)	(2.509)
N	250,594	288,299	91,656	106,055
Mean	17.40	22.23	17.40	22.23
First Stage F-stat	42.76	301.26	17.18	18.92
Individual Controls	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	Yes
Relative Year FE	Yes	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

Notes: This table reports the coefficients from the difference-in-differences instrumental variables specification (DID IV), which first estimates Equation 7 for FEMA Individuals and Households Program (IHP) aid. In both specifications, I control for the average size of the fires within the county (in thousands of acres), the age category of the individual, whether she is married, whether she has a college education, and the duration of time she lives in the census block. I also include relative year, calendar year, and individual fixed effects. The county controls I include are the ones I use in Table 6, in which I estimate Equation 8 using a variety of county-level data sources from the California Open Data website. These county-level controls are the expenditures data from California's County Financial Transactions Report on Expenditures, the food stamps data come from CalFresh, and the tax data from the California Department of Tax and Fee Administration. I cluster the regression at the county level.

C California Background

C.1 Insurance

The insurance landscape in California also may cause distortions in people's location decisions. For many years, Californian insurance companies were not able to incorporate forecasting models into their prices due to their lack of transparency so that they could only rely on historical fires (Frazier, 2021). As a result, right after a fire occurs, the premiums of the area will increase, though the fire risk decreases immediately after a fire. Insurance companies also calculate damages in a way that disincentivizes migration. In 2021, California insurance companies were required to include the value of the land of destroyed property in their payouts if the person chose to relocate (CDI, 2021). Before this, there would be large differences in the value of the land for those who chose to move away vs. rebuild, and this 2021 amendment was specifically put in place to address this discrepancy. Additionally, California state insurance regulators do not allow for the costs of reinsurance risk, which are secondary insurance contracts with global insurers to hedge against correlated or severe risks such as wildfires, to be included in insurer rate requests. Keys and Mulder, 2024 finds that reinsurance costs have doubled from 2018-2023. These factors compound to dissuade private insurance carriers to stay within the California insurance market. As of June 2024, State Farm and All State have noted that they will not write new homeowner policies in the state Jacobson, 2024. Since State Farm uses the most granular wildfire risk algorithms and has the largest market presence in high-risk areas (Boomhower et al., 2024), their withdrawal from the insurance market will have a large impact on homeowners.

Insurance companies in California respond to wildfires by increasing their prices or cancelling policies, which theoretically will make it more expensive to stay in these areas. Incumbent residents may be more likely to move out, and newcomers may find it more difficult to obtain a mortgage to move in. For those who stay but do not have insurance (i.e. if they already paid off their homes so do not need a homeowner insurance policy, which is required for mortgages), experiencing another wildfire without the protection of insurance may have an even larger negative impact on the individual. Although California issued a mandatory one year moratorium on non-renewals on insurance companies after a wildfire beginning in 2019, this protects certain zip codes and requires a Governor emergency declaration for a nearby fire (CDI, 2021).

California's insurance landscape incentivizes rebuilding the home. Many home insurance payouts are also contingent on rebuilding the home, drawing people back to the burned area. Until 2021, Californian insurance companies would not count the value of the land in their payout if the owner were to move away (Issler et al., 2024). Because the individual could gain hundreds of thousands of dollars more if they decided to stay, this would discourage migration. The California Insurance Commissioner, Ricardo Lara, issued a memo that provides an example of how some policyholders are penalized for choosing to exercise their right to purchase a home at a new location rather than rebuild. "If the insured's home was fully destroyed and it is determined that the cost to rebuild at its original location (up to policy limits) is $400,000, and the cost to purchase the new property (including the home and the land) at a new location is at least $400,000, the insured would receive $400,000 to purchase an existing home at the new location. However, if the cost to purchase the new property is $400,000 (including the home and the land and assuming the land value is $200,000), some insurers would only pay $200,000" (Lara, 2019). However, since insurance companies are not allowed to use predictive models to price their products, they rely on historic wildfire incidents to justify higher prices. That means that although immediately after a wildfire occurs, the risk of another one is lower because the fuel in the area has been burned, these areas will experience an increase in their insurance prices. This increase could price out individuals who either decide or can no longer afford to live in that area.

C.2 Tax Benefits

Another California-specific institutional detail is Proposition 19, which includes an allowance for homeowners whose home is destroyed by a wildfire to take their tax burden if they were to purchase a new home in California. This follows a series of similar legislations over the years, which allowed this tax burden reallocation within the burned county as well as to specific counties throughout California (CBPC, 2020; Dillon, 2020; BOE, 2021).

The most recent iteration of this legislation, Proposition 19, passed on November 3, 2020 and became effective on December 16, 2020. It allows homeowners who are over 55, severely disabled, or whose homes are destroyed by natural disasters to transfer their property tax bill from one home to another of any value anywhere in the state. Individuals who are in these categories and occupies their home as a principal residence and purchase a replacement home within two years qualify for this tax benefit (BOE, 2021). This builds upon Proposition 13, which limits the property tax for a home every year to 1% of the property's value on the date of purchase. This prohibits the property from being reassessed for a new base year value unless the property is sold or construction is done to the property. These factors keep the property tax of the house far lower than the market value (CBPC, 2020).

Proposition 19 has been criticized for disproportionately benefitting older, white, and wealthy California homeowners, with disaster-affected homeowners comprising under 1% of those eligible for tax relief (Dillon, 2020; Kimberlin and Kitson, 2020). However, the legislation requires the state to put the increased tax revenues that may be generated into wildfire response (Kimberlin and Kitson, 2020). This legislation could incentivize people to stay within California to take advantage of keeping their, likely lower, tax burden. It could also help those who are able to afford it to move to more expensive homes – perhaps in safer areas – without incurring a higher property tax burden.