

Fire, Labor, and Recommitment: Investigating the Relationship Between Wildfire Exposure and Recidivism Among Fire Camp Participants

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Abstract

This paper investigates the relationship between fire exposure and recommitment among incarcerated individuals participating in California's fire camp program. While these camps are often shown as rehabilitative, their function as a prison first and camp second complicates this narrative. Using logistic regression models and exact matching techniques, I exploit variation in fire severity, measured in acres burned per person, as an exogenous proxy for differences in inmate labor type. The analysis finds that individuals exposed to higher fire severity, and thus more likely to engage in active firefighting, have significantly lower odds of recommitting than those in camps with less fire exposure, which tend to emphasize grade work, though the data only captures recommitment to fire camps. These findings are robust across multiple model specifications and matching strategies. This suggests that programs framed around purpose and building self worth, rather than discipline and building work ethic alone, may reduce recommitment.

1. Introduction

1.1 Background

The United States, the "world's warden," has 4% of the global population but holds 16% of the world's incarcerated population (Vera Institute, 2021). With the highest recidivism rate globally, the U.S. currently houses around 2 million people in state and federal prisons or local jails at any given time (Prison Policy Initiative, 2022). Since 1973, the incarcerated population

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has surged by over 500%, rising from roughly 200,000 to a peak of 1.6 million in 2009 (Sentencing Project, 2023).

Historically, the United States maintained relatively low incarceration rates, around 110 per 100,000 individuals prior to the 1970s. However, starting in 1972, incarceration rates rose significantly, growing annually by 6% to 8% through the year 2000 (Travis, Western, & Redburn, 2014). Between 1990 and 1995, all states—except Maine—increased their prison populations, ranging from 13% in South Carolina to 130% in Texas. This increase was not primarily due to rising crime rates but rather to a shift toward more punitive criminal justice policies—particularly during the 1990s and early 2000s, often cited as the most punitive era in U.S. history (Enns, 2016). A substantial portion of the surge came from incarcerating individuals for technical violations of parole and probation rather than for new criminal offenses. By 1999, only about 60% of prison admissions were for new court convictions; the remainder resulted from supervision failures (Duggan & Piehl, 2004). Furthermore, individuals convicted of violent crimes such as murder or assault are less likely to return to custody than those convicted of property crimes like burglary or theft. These trends suggest that the expansion of incarceration in the U.S. has been driven more by policy choices than by a rise in violent or serious crime.

Scholars attribute this shift mainly to political and legislative changes. While federal laws like the Sentencing Reform Act of 1984, the Anti-Drug Abuse Act of 1986, and the Violent Crime Control and Law Enforcement Act of 1994 significantly impacted sentencing practices, state-level policies played an even greater role (U.S. Congress, 1983-1986; 1993-1994). Economists Dan O'Flaherty and Rajiv Sethi, in their book *Shadows of Doubt* (2019), emphasize that mass incarceration resulted from a complex interplay of policies, with state legislatures aggressively implementing harsher mandatory minimum sentences, eliminating parole, and broadening felony classifications. These policy changes moved sentencing away from

individualized judgment, replacing it with stricter, universal punishments. In particular, Truth-in-Sentencing laws, required longer prison terms and were a turning point at both the state and federal level to a more punitive approach.

Although "justice" is a broad concept—much like "education," which can be defined without mentioning mathematics or spelling—the treatment of rehabilitation in the U.S. Sentencing Guidelines reflects a shift toward a more punitive vision of justice. For example, the U.S. Sentencing Guidelines (1984–1987) explicitly state that "imprisonment is not an appropriate means of promoting correction and rehabilitation" (USSC §1A1.1). Furthermore, in considering sentence reductions, the guidelines declare that "rehabilitation of the defendant alone shall not be considered an extraordinary and compelling reason" (USSC §1B1.13). At the state level, rehabilitation is similarly deprioritized, as seen in truth-in-sentencing laws. Although rehabilitation is not absent from legal frameworks, its role in both federal and state definitions of justice is limited—consistently treated as secondary to punishment.

One country that has shifted its focus to a rehabilitative system is Norway, boasting the lowest recidivism rates in the world, around 20% after 3 years (Denny, Meagan, 2016). This is a stark comparison to the United States, where 66% of individuals are rearrested within three years (BJS, 2021). However, the United States was not always so distant from Norway: in the 1990s, Norway's recidivism rate was closer to 70%. Norway's improvement is primarily due to its focus on rehabilitation and reentry rather than punishment. Norway has eliminated life sentences and imposes a maximum sentence of 30 years, with the vast majority of incarcerated individuals serving sentences of one year or less. Figure 1.1 illustrates the incarceration rate per 100,000 people. As previously stated, the U.S. fluctuated around 110 per 100,000 individuals prior to the 1970s before experiencing a drastic increase. In contrast, the graph shows that Norway and other Western European countries maintained stable incarceration rates from the 1980s to 2012,

consistently staying below 100 per 100,000 individuals. Norway's rehabilitative approach focuses on restorative justice, providing incarcerated individuals with vocational training, education, and support services that increase the chances of successful reintegration into society.

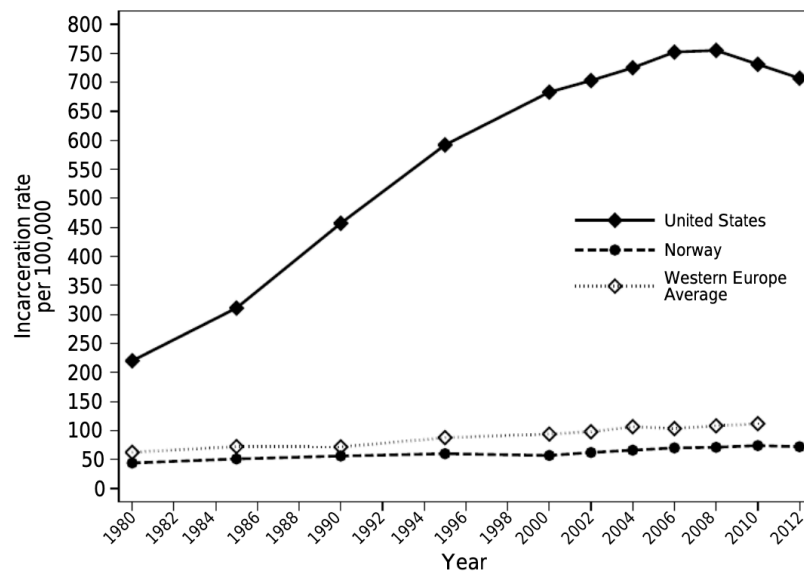


Figure 1.1: Incarceration Rate per 100,000 people (total population) from 1980-2012

Source: Institute for Criminal Policy Research

Note: “Western Europe” refers to a population-weighted average of the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

1.2 Fire Camps

This paper investigates whether the severity of fire exposure within California's fire camp system, measured by variation in acres burned, is associated with differences in recidivism. By doing so, I aim to assess whether firefighting contributes to improved post-release outcomes or whether other factors drive the perceived benefits of these programs. While the California Department of Corrections and Rehabilitation (CDCR) suggests that participation in firefighting promotes personal growth and rehabilitation among incarcerated individuals (see Figure 1.2), this

claim has not been empirically tested. It remains possible that these programs primarily capitalize on incarcerated labor, assigning individuals to dangerous, low-compensated roles without delivering long-term benefits. To evaluate this relationship, I treat variation in fire exposure as a random treatment across fire camps and examine recommitment rates as the primary outcome to determine whether greater fire exposure is associated with improved post-release trajectories.

Inspired by the Norwegian models, California has begun adopting similar rehabilitative methods to enhance its vocational training programs, including fire camps, which have been a part of the prison system since 1946. According to the California Department of Corrections and Rehabilitation (CDCR, 2019), California leaders are learning from Norway's progressive prison system to further develop and improve these programs. Currently, there are 35 fire camps jointly operated by CAL Fire and the California Department of Corrections. In contrast to the large barbed-wire prisons that house thousands of incarcerated individuals, these fire camps are small, accommodating anywhere from 90 to 120 incarcerated individuals each. They constitute approximately 2.5% of California's total prison population (Goodman, 2012).

Incarcerated individuals must voluntarily opt into the program and face no penalties for opting out. To qualify, participants must be classified under minimum/medium custody, indicating a low-security status based on consistent good behavior, and have eight years or less remaining on their sentence. Certain convictions automatically disqualify candidates, including arson, rape, and sex offenses, as well as cases involving escape history or high notoriety. Additional exclusions are if the participant has any active warrants, unresolved legal issues, and medical conditions that prevent them from doing physical labor. However, a flexible security provision allows incarcerated individuals convicted of violent crimes, such as armed robbery, to participate, provided they meet the minimum security requirement (CDCR, 2019).

Upon meeting the criteria, incarcerated individuals are then transferred to Sierra Conservation, where they must pass the physical fitness test and complete CAL FIRE's Firefighting Training (FFT) program. Training consists of four days of classroom training and four days of field training taught by CAL FIRE staff. Upon completion, participants are certified as wildland firefighters, but they are not immediately transferred to a fire camp. Placement depends on space availability, and individuals often spend weeks or even months waiting at Sierra before being assigned to a camp where they serve the remainder of their sentence.

Due to the nature of the work, participants receive slightly increased pay compared to incarcerated individuals in traditional, walled prisons. Figure 1.2 depicts the pay rates for fire camp participants, while Figure 1.3 illustrates the pay rates for those in conventional prisons across California.

<u>Grade Inmates (Firefighters)</u>	<u>Max Daily Rate</u>
<u>Grade 1</u>	<u>\$10.24</u>
<u>Grade 2</u>	<u>\$7.80</u>
<u>Grade 3</u>	<u>\$6.68</u>
<u>Grade 4</u>	<u>\$5.80</u>

Figure 1.2: Fire Camp Maximum Daily Wages by Skill Level

Source: California Department of Corrections and Rehabilitation “Inmate Pay Rates Schedules and Exceptions,” 2023.

Note: Incarcerated individuals in the Fire Camp programs are categorized into four grade levels (1-4) based on their skill levels, with Grade 1 being the most skilled and Grade 4 the least. Greater skill corresponds to higher maximum daily pay rates.

<u>Pay Scale Levels</u>	<u>Minimum/Maximum Per Hour for Hours Worked</u>
<u>Level 1(DOT 9)</u>	
<u>Lead Person</u>	<u>\$0.64-\$0.74</u>
<u>Level 2 (DOT 7-8)</u>	
<u>Special Skill</u>	<u>\$0.38-\$0.64</u>
<u>Level 3 (DOT 5-6)</u>	
<u>Technician</u>	<u>\$0.30-\$0.48</u>
<u>Level 4 (DOT 3-4)</u>	
<u>Semi-Skilled</u>	<u>\$0.22-\$0.36</u>
<u>Level 5 (DOT 1-2)</u>	
<u>Laborer</u>	<u>\$0.16-\$0.26</u>

Figure 1.3: Regular Prison Minimum and Maximum Hourly Rate by Skill Level

Source: California Department of Corrections and Rehabilitation “Inmate Pay Rates Schedules and Exceptions,” 2023.

Note: Incarcerated individuals in regular prisons are categorized into five skill levels (1-5), with Level 1 being the highest skill level and Level 5 the lowest. Greater skill corresponds to higher hourly pay rates.

When converting daily earnings into hourly wages, assuming a 10-hour workday, fire camp participants earn between \$0.58 and \$1.02 per hour. In contrast, the lowest-paid individuals in walled prisons earn between \$0.16 and \$0.26 per hour, while the highest-paid earn between \$0.64 and \$0.74 per hour. This slight increase in wage is likely not a significant incentive for participation.

The environment within these fire camps is significantly different from traditional prisons. Stone walls and gun towers are replaced by wooden signs reading "camp boundary ends here," creating an open and less restrictive prison setting. Additionally, the non-nutritious, poor-tasting food typically associated with incarceration is replaced with "home-cooked" meals prepared by incarcerated individuals themselves. This improves the quality of life as well as reducing violence within the camps, as participants are less inclined to jeopardize their privileges. However, the higher standards of living are not free. Most participants work five or more days a week, engaging in hard manual labor. According to the CDCR website, "the conservation camps' mission is 'to provide the cooperative agencies with an able-bodied, trained workforce' for

firefighting, other emergencies, conservation projects, and 'local community service projects.'" Additionally, the website reports that incarcerated individuals contribute approximately three million person-hours annually to firefighting and emergency aid, along with about seven million person-hours to various project works (California Department of Corrections and Rehabilitation, 2012).

California's fire camp programs operate yearly, allowing for variability in fire severity. Peak fire seasons typically demand more firefighting and fire suppression work. In contrast, non-peak seasons involve more support tasks such as trail clearing, grade work, and flood mitigation. This natural variability in fire intensity introduces an exogenous component, seasonal fire severity, that influences the type and intensity of inmate labor without being directly tied to individual characteristics. As such, it provides a useful lens for evaluating the potential effects of fire camp participation on recidivism.

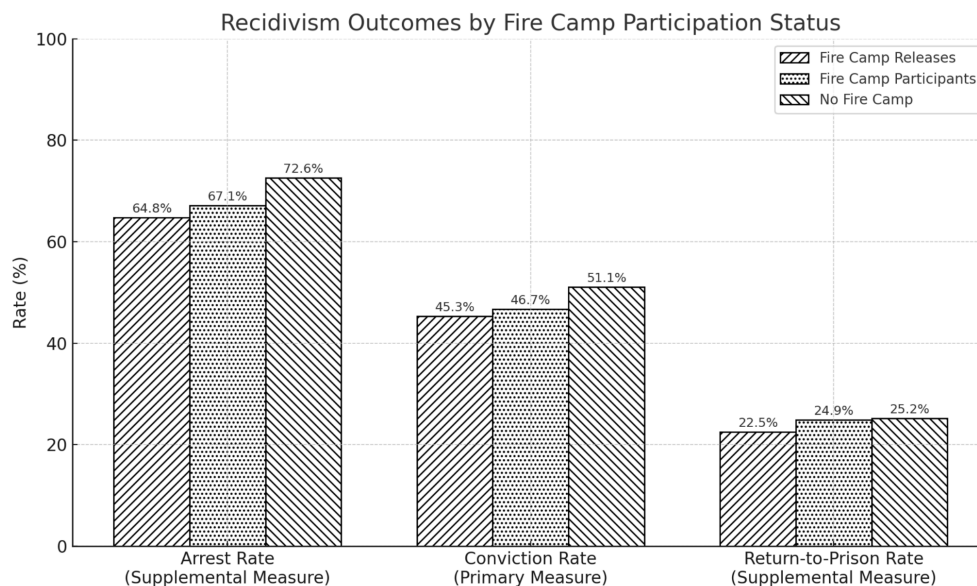


Figure 1.4: 2016-2017 Outcomes for Fire Camp vs. Non-Fire Camp Participants

Source: California Department of Corrections and Rehabilitation "Recidivism Rates for Fire Camp Participants Released from CDCR in Fiscal Year 2016-17"

Figure 1.4 shows that, in raw comparisons, those who have fire camp experience are less likely to recommit than other incarcerated individuals. At first glance, this appears to support my hypothesis but this is not necessarily true. Participation in these programs is voluntary, potentially introducing selection bias; participants might inherently differ from non-participants in motivation or background. Even if the program has a causal effect, it remains unclear whether the experience of active firefighting itself or simply the overall environment of the camp drives improved outcomes. Given the scale of incarceration and the increasing frequency of forest fires, clearly understanding these distinctions is critical.

2. Literature Review

Work has been a key component of the prison experience throughout the United States' history of incarceration. However, the question of whether it is rehabilitative or exploitative remains prevalent. From the institutional perspective, inmate labor reduces operating costs and lowers idleness. Proponents also argue it teaches basic work habits such as time management, discipline, and accountability (Maguire, Flanagan, Thornberry 1988). With many incarcerated individuals lacking a sufficient work record, teaching the basics of "work ethic" is seen as an important benefit of these programs. However, whether this exposure leads to better post-release outcomes remains uncertain.

In their study *Prison Labor and Recidivism*, Maguire, Flanagan, and Thornberry (1988) found that while prison industry participants initially showed lower rates of recidivism, these differences disappeared after accounting for background characteristics. This suggests that the apparent benefits of prison labor may reflect selection bias, which could be tied to individuals'

skill levels or internal motivation for change. Their findings raise questions about whether carceral labor provides real-world, marketable skills or just fills time. Phillip Goodman, Professor of Sociology at the University of Toronto Mississauga, argues that fire camps reflect a newer, pared-down model of rehabilitation: one focused less on specific skills and more on abstract ideas like work ethic and personal responsibility. This reflects a broader neoliberal logic in which responsibility for rehabilitation is shifted onto individuals, framing success or failure as a matter of personal choice rather than structural constraint. These concerns are important in the context of California's Fire camp program, where incarcerated individuals perform high-risk labor for a few dollars a day without a guaranteed pathway to post-release employment despite the program's rehabilitative image. In *The Culture of Control* (2001), David Garland observes that "rehabilitation programmes no longer claim to express the overarching ideology of the system, nor to be the leading purpose of any penal measure." Goodman echoes this sentiment, noting that rehabilitation is often considered "dead or on life support." Most studies, he observes, reduce rehabilitation to a question of recidivism, overlooking more subjective dimensions such as personal growth or self-worth.

In his study *Hero and Inmate: Work, Prisons, and Punishment in California's Fire Camps* (2012), Goodman conducts interviews with both incarcerated individuals and correctional officers to explore, at a micro-level, whether these programs are rehabilitative in practice. He conducts two sets of interviews with participants, one focused on their experiences performing routine "grade work" and another centered on their roles during active firefighting, to draw distinctions between the nature and perceived value of each type of labor. Grade work includes projects such as "maintenance at a local golf course, cleaning trash along the highway, using sledgehammers to demolish a stone grill at a local park..." Approximately one-third of the incarcerated individuals interviewed characterized this labor as "hard manual work," a finding reflected in broader survey

data, where 33.3% of inmates identified this as the primary frame for grade work. Others viewed it more positively, with 17.8% citing the chance to get outdoors or go to work and 11.1% emphasizing the development of a work ethic. One interviewee, Potter, suggested the structure could have lasting benefits: "I think it can. You know, teach someone to work on a schedule. And if you work on a schedule, you're less likely to get caught up again." However, views diverged sharply on the question of exploitation. While correctional officers universally rejected the idea, responding with statements like, "For sure it's not labor exploitation. It's not." incarcerated participants offered a different perspective. Ten out of the 45 individuals interviewed described the labor as "slavery," with almost all of the participants viewing it as exploitative, particularly focusing on the low wages. Rather than viewing their compensation as a reward for a job well done, many interpreted it as a reflection of how little their labor was valued. As Goodman notes, incarcerated individuals were more troubled by the underlying message of their wages: "namely that their labor is nearly worthless." These shared ideas run counter to the fire camps' stated mission of promoting "self-esteem and self-sufficiency." Overall, the grade work was seen as potentially beneficial for discipline and structure but also deeply exploitative in its implementation.

When asked about the firefighting work, responses were more positive. A common theme across both staff and incarcerated individuals was a shared sense of pride in the work performed by inmate fire crews. In the survey, 42.2% of inmates described firefighting as "intense, hard, and/or dangerous," 13.3% framed it as a unique experience, and another 13.3% saw it as a way of giving back to the community. By contrast, only 2.2% of inmates described grade work as a form of public service. Firefighting was far more frequently associated with pride, recognition, and purposeful contribution. Many incarcerated individuals described the experience as empowering, holding a new self-image not of an inmate or laborer but of a hero. Goodman highlights how this

shift in identity, from prisoner to public servant, allowed participants to temporarily break free from the stigma of incarceration and view themselves as valued contributors. While grade work often reinforced their status as prisoners in the eyes of the public, firefighting offered something different. One incarcerated individual said, "When not fighting fires, stereotypes of inmates as rapists and murderers resurface, and people once again dislike and fear camp inmates." Several others had similar thoughts, noting that during grade work, they were seen simply as "inmates," but while fighting wildfires, they were viewed as "heroes." This suggests that firefighting may create a sense of purpose and belonging that grade work rarely provides. Danielle Allen offers a related but more intimate account in *Cuz* (2017), describing her cousin Michael's time in a California fire camp as one of the only moments in his incarceration when he felt genuinely human again. For Allen, the camp offered a rare intersection of structure, responsibility, and public legitimacy, conditions that allowed her cousin to experience a sense of personal dignity and value.

Goodman concludes that those "doing time" in a fire camp view grade work and firefighting as "partially exploitation and partially something to appreciate as good, useful, or at least better than the alternative." Grade work, while physically demanding and often perceived as demeaning, is valued primarily for instilling a sense of work ethic. In contrast, firefighting is more likely to boost confidence and enhance self-worth, as incarcerated individuals see their contributions publicly recognized as heroic. The perceived exploitation in grade work is tied largely to low wages and the difficult nature of the labor, whereas the exploitative aspects of firefighting stem from the conditions under which they work, doing the dangerous, dirty tasks that many civilian firefighters avoid, not necessarily the pay.

Gendreau et al.'s (1979) study *Self-Esteem, Incarceration, and Recidivism* offers a complement to the findings of Goodman (2012). The researchers examined a sample of 82

first-time incarcerated males, all approximately 18 years old and averaging a ninth-grade education level. Self-esteem was assessed two to four weeks after incarceration, with a follow-up evaluation conducted six months later. To measure self-esteem and related psychological traits, the study employed multiple instruments: the Self-Esteem Inventory (SEI)², the Adjective Check List (ACL)³, and selected scales from the Minnesota Multiphasic Personality Inventory (MMPI)⁴ including the K, D, Pt, and Pd scales. These tools captured a range of self-perceptions, moods, and antisocial attitudes relevant to post-release outcomes. While they found that the broad SEI measure was not significantly related to reconviction, certain components of self-esteem were. In particular, the MMPI Pd scale and ACL traits such as autonomy, nurturance, and counseling readiness were strongly associated with recidivism, especially when measured near the end of incarceration. Self-esteem scores taken six months into incarceration were the strongest predictors of post-release behavior, with the regression model yielding an R value of 0.63 and correctly classifying recidivism outcomes 82.4% of the time. These findings highlight that self-esteem is multi-dimensional, not easily captured by a single scale, and underscore its power as a predictor of post-release outcomes. This suggests that programs focused on building self-worth and purpose, such as the experiences in high-fire camps, may be more effective at reducing recommitment than programs grounded solely in work ethic or discipline.

Although the California Department of Corrections and Rehabilitation (CDCR) frequently describes its fire camp program as a “win-win-win” solution (saving money, helping incarcerated individuals, and improving their public image) it historically avoided measuring the program’s effectiveness using recidivism. Since then, it has published comparisons between fire camp

² The SEI is a general measure of global self-esteem developed by Bennett et al. (1971), widely used in correctional settings.

³ The ACL, developed by Gough and Heilbrun (1965), includes 24 scales capturing diverse personality dimensions, including autonomy, personal adjustment, and nurturance.

⁴ The MMPI scales used were Pd (psychopathic deviate), Pt (psychasthenia), D (depression), and K (defensiveness)—common proxies for self-concept and antisocial tendencies.

participants and individuals incarcerated in traditional (walled) prisons, consistently reporting an average two percentage point lower recidivism rate for those in fire camps. But, this figure is likely biased. Participation in fire camps is voluntary and restricted to individuals serving sentences of eight years or less, who must also score below a threshold on a classification system that lists them as either low or medium security. As a result, the observed differences in recidivism may reflect selection effects rather than the impact of the program itself. My study addresses this gap by using variation in fire severity as a way to isolate the effects of firefighting within the camp context. Specifically, I compare individuals exposed primarily to grade work (low fire exposure) with those who engage in active firefighting (high fire exposure). This allows me to explore whether post-release outcomes are better explained by the structure and discipline of labor (work ethic), or by shifts in self-image and self-worth tied to performing heroic, socially recognized work.

3. Data and Methodology

3.1 Methodology

My analysis examines whether the intensity of fire exposure during incarceration is linked to differences in post-release outcomes. If my hypothesis is correct, that participation in active fire fighting leads to better outcomes than routine grade work, then individuals exposed to more severe fire conditions should exhibit lower rates of recommitment. To investigate this, I draw on variation in fire activity across camps and years, using individual-level data on sentence length, demographics, and post-release outcomes to estimate the relationship between fire exposure and recidivism.

I begin with a general estimating equation of the form:

$$Recommit = \alpha + \beta \cdot FIRE + Controls + \varepsilon$$

where recommitment is the outcome, and fire exposure is measured using either a binary indicator for high fire, log acres burned, or shocked log acres.

My primary regression specification is given by:

$$\Pr(\text{Recommit}_{it} = 1) = \Lambda(\beta_0 + \beta_1 \text{High Fire}_{it} + \mathbf{X}'_{it}\boldsymbol{\beta} + \gamma_{c[i]})$$

In this model, the dependent variable is recommitment, coded as a binary outcome (one if the individual recommits, zero otherwise). I estimate a logistic regression model to account for the nonlinear relationship between the covariates and the probability of recommitment. The primary independent variable is a binary indicator for high fire exposure (1 for high exposure, 0 for low), accompanied by a set of control variables including gender (female), race (non-white), sentence length, education, industry experience, job training, program participation, and self-help engagement. With the exception of sentence length, all control variables are binary. I also include camp-level fixed effects to account for unobserved heterogeneity across camps. Given that individuals are randomly assigned to available camps after eligibility screening, fire exposure can be treated as random within the fire camp population. A two-way ANOVA confirms that race and gender vary significantly across camps, justifying the inclusion of camp-fixed effects, while fire exposure varies primarily within camps over time. I therefore exclude year-fixed effects, as fire exposure is not systematically determined by year.

High fire exposure is defined by calculating acres burned per person, measured as the total number of acres burned in the counties associated with each fire camp, divided by the camp's incarcerated population. To normalize the distribution, I take the natural logarithm of this value. Because several of the 42 camps share overlapping locations, I collapse them into 30 unique camp entries. These are then ranked based on their log-transformed fire exposure, and the top 15

are classified as 'high fire' (High Fire = 1), while the bottom 15 serve as the low fire comparison group (High Fire = 0).

High Fire, being a binary variable, may oversimplify the variation in fire exposure across camps. To address this, I test a continuous measure of fire exposure: the log of acres burned per person. This specification allows me to capture more of the variation in fire intensity across individuals. The regression model is specified as follows:

$$\Pr(\text{Recommit}_{it} = 1) = \Lambda \left(\beta_0 + \beta_1 \log(\text{Acres Burned Per Person}_{it}) + \mathbf{X}'_{it}\boldsymbol{\beta} + \gamma_{c[i]} \right)$$

The final model uses the log of shocked acres burned per person as the main independent variable. To construct this, I first calculate a baseline of average acres burned per county, then compare each year from 2014 to 2018 against that baseline to capture deviations or “shocks” in fire exposure. I then divide these shocked values by the number of incarcerated individuals at each fire camp and take the log, as in previous models. This approach aims to capture meaningful fluctuations in fire intensity, for example, a county that consistently experiences similar acres burned per year may not reflect a true change in fire conditions. By focusing on deviations from typical fire levels, this specification helps isolate the effects of unexpected fire severity on post-release outcomes. The model is as shown:

$$\Pr(\text{Recommit}_{it} = 1) = \Lambda \left(\beta_0 + \beta_1 \log(\text{Shocked Acres Per Person}_{it}) + \mathbf{X}'_{it}\boldsymbol{\beta} + \gamma_{c[i]} \right)$$

Lastly, I conducted an exact matching method, pairing individuals in high-fire camps with those in low-fire camps who were identical across key characteristics: controlling offense, race, sentence length, education, industry, job, self-help participation, and program involvement. The only difference between matched individuals was their exposure to fire severity, with high-fire camps classified as the top half of log acres burned per person per year and low-fire camps as the

bottom half. I then relax the matching criteria, first allowing race to vary, then race and gender, and finally matching only on sentence length and offense type. My goal is to leverage this direct comparison method to better isolate the impact of fire severity on recommitment outcomes. Unlike the regression models, which impose a functional form on the data, exact matching offers a nonparametric alternative that relaxes these assumptions and serves as a robustness check for my main results.

3.2 Data

This paper uses a custom dataset obtained from California's Department of Corrections and Rehabilitation (CDCR), along with data sourced from the California Department of Forestry and Fire Protection (CAL FIRE) website. The dataset encompasses records of individuals formerly or currently incarcerated in fire camp prisons from 2014 to 2024. It includes de-identified inmate numbers, gender, current age, race, offense leading to arrest, aggregate sentence length, number of CDCR commitments⁵, and, if applicable, their assigned fire camp placement during the specified period. Recombitment is used as a binary variable, equal to one if the individual returned to CDCR custody and was placed in a fire camp again and zero otherwise. This was determined by filtering for repeated de-identified inmate numbers; if an individual appeared more than once in the dataset, they were classified as having recommitted. The dataset also includes five variables that are used as binary indicators in my model (zero if not participated in and one if participated in), representing different forms of inmate engagement: job, education, industry, program, and self-help. Job refers to institutional work assignments within the prison, such as kitchen work, janitorial duties, clerical roles, and maintenance, but excludes specialized industry jobs and fire camp work. Education has academic and vocational training programs, including

⁵ The number of CDCR commitments represents the total number of times the individual has been to prison on a new conviction.

GED courses, college classes, and career technical education. Industry covers employment within the Prison Industry Authority (PIA), where inmates engage in manufacturing, construction, or other trade-based jobs. Program consists of structured rehabilitative courses, such as cognitive behavioral therapy, substance abuse treatment, and life skills classes, which are often mandated as part of reintegration efforts. Finally, Self-Help refers to voluntary, peer-led initiatives like Alcoholics Anonymous (AA), religious study groups, and mentorship programs.

The dataset consists of 32,771 entries, of which 30,465 are unique, and 2,305 are repeated, indicating that some individuals participated in fire camps multiple times. For this study, I focused on individuals who entered fire camps between 2014 and 2018, applying the following criteria: they must have entered a fire camp in this period and had an aggregate sentence length of 108 months (2014), 96 months (2015), 84 months (2016), 72 months (2017), or 60 months (2018) or less. This ensured that each individual had at least one-year post-release, providing sufficient time to observe potential recommitments. I limited the analysis to 2018 because including 2019 and later years would not have increased the sample size by much. For example, in 2019, only individuals with sentences of 48 months or less would be eligible for observation, substantially narrowing the population. By not including the years 2019-2024 under the same conditions stated above, I missed out on an additional 2,244 observations.

A limitation of this approach is that the dataset does not include the exact date of fire camp entry. As a result, an individual with a 108-month sentence may have entered the fire camp in 2014 with only 8 months left to serve, meaning my observation window could have been expanded by adjusting the aggregate sentence length threshold. For example, if I included all possible sentence lengths ranging from 0 to 288 months for 2014, the number of entries would increase from 1,997 to 2,225—an increase of 228 observations. Doing this across each individual year led to similar increases in observations, which had minimal impact on the dataset. Limiting

sentence lengths in this way allowed me to maintain consistency in the observation window and to control for the amount of time individuals have had post-release before potentially recommitting.

After filtering, the dataset contained the following unique entries and demographic breakdowns:

2014 (1,997 unique entries)

- Gender: 1,935 males (96.90%), 62 females (3.10%)
- Race: 672 Hispanic (33.65%), 578 White (28.94%), 497 Black (24.89%), 250 Other (12.52%)

2015 (2,700 unique entries)

- Gender: 2,411 males (89.30%), 289 females (10.70%)
- Race: 1,028 Hispanic (38.07%), 834 White (30.89%), 550 Black (20.37%), 288 Other (10.67%)

2016 (1,956 unique entries)

- Gender: 1,766 males (90.29%), 190 females (9.71%)
- Race: 784 Hispanic (40.08%), 585 White (29.91%), 351 Black (17.94%), 236 Other (12.07%)

2017 (2,361 unique entries)

- Gender: 2,086 male (88.35%), 275 females (11.65%)

- Race: 985 Hispanic (41.72%), 674 White (28.55%), 456 Black (19.31%), 246 Other (10.42%)

2018 (2,386 unique entries)

- Gender: 2,181 males (91.41%), 205 females (8.59%)
- Race: 1,092 Hispanic (45.77%), 607 White (25.44%), 469 Black (19.66%), 218 Other (9.14%)

In total, the dataset consists of 11,400 unique entries. The demographic breakdown is as follows:

- Gender: 10,379 males (91.04%), 1,021 females (8.96%)
- Race: 4,561 Hispanic (40.01%), 3,278 White (28.75%), 2,323 Black (20.38%), 1,238 Other (10.86%)

This five-year window provides the necessary variation to capture fluctuations in acres burned across multiple years. Given that only three fire camps are designated for females, the female population in the dataset is significantly smaller than the male population.

Another variable initially considered was age. However, current age data was missing for the majority of entries, causing me to exclude it from the model. A variable I contemplated adding is whether the individual's crime is categorized as violent or non-violent. However, the dataset only provides a broad offense code. For example, offenses under the Health and Safety (HS) code can range from drug possession to administering poison, making it difficult to distinguish crime severity with precision. The number of CDCR commitments was initially considered as a control variable but ultimately excluded from the model, as it is mechanically correlated with the dependent variable, recommitment. Since recommitment itself reflects new terms, including this

measure would inherently bias the analysis and potentially inflate the significance between number of commitments and recommitments.

A key limitation of my dataset is that the dependent variable, recommitment, only captures individuals who return to a fire camp following release. If an individual recommit and is sent to a traditional (walled) prison instead, this is not reflected in the data. Because the dataset only includes individuals assigned to fire camps, I am unable to track recommitments that occur outside of this context. As a result, any observed reduction in recommitment should be interpreted as a reduction in the likelihood of returning to a fire camp, rather than a reduction in overall recidivism. This distinction is important, as the findings may reflect changes in assignment or eligibility for fire camps rather than actual behavioral or rehabilitative outcomes.

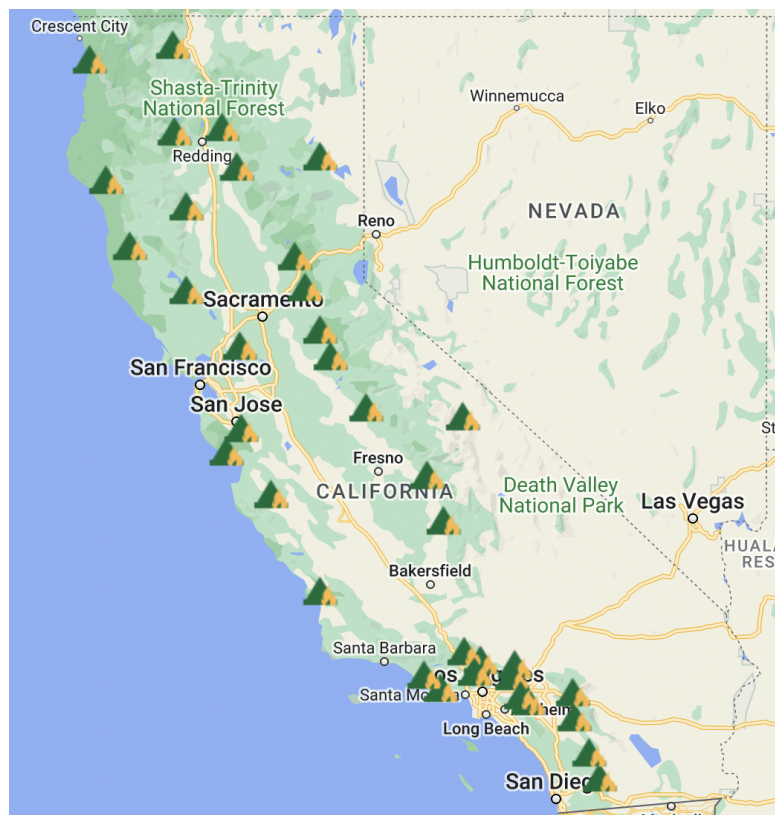


Figure 3.2.1: Geographic distribution of fire camps across California

The data from CAL FIRE included the incident name, county/counties affected, start date, acres burned, and containment status. To obtain this data, I employed two methods. First, I used a file on CAL FIRE's website, which contained fire data from 2013 to 2024, using Python to extract information on the number of fires and total acres burned per county per year, as these were the key variables of interest. I then manually scraped their website, which reports individual fire incidents per county per year.

However, I observed discrepancies between these two methods. The data from the file reported lower totals for both acres burned and the number of fires compared to the manual scraping method, which in turn provided figures lower than what the website itself reported as the overall totals. For example, in 2014, the file recorded 296,982 acres burned and 76 fires, while manual scraping produced 440,081 acres burned and 115 fires. Meanwhile, CAL FIRE's website reported 625,540 acres burned across 7,233 fires for that year.

This discrepancy could be explained by a statement on CAL FIRE's website, which notes that "no information will generally be provided on incidents if the fire burns less than 10 acres." Additionally, the total numbers reported on the website may account for all fires fought by various fire departments, while the detailed listings may only include fires under CAL FIRE's jurisdiction. As a result, I relied on the most reliable figures for acres burned, which came from the manually scraped data.

I compiled a list of 104 counties and joint counties from the file and scraped CAL FIRE's website for 2014 data. Rather than using the number of fires, which reflects frequency rather than intensity, I chose the number of acres burned per county as a measure of fire severity. I then categorized the fire camps based on the counties in which they operate and matched the corresponding acres burned in those areas. Some camps operate across multiple counties—for example, Ishi Camp covers Tehama, Glenn, Shasta, and Plumas. In such cases, I treated the camp

as a multi-county entry and summed the total acres burned across all associated counties. Initially, I considered the possibility of double counting since some camps, such as Valley View, only operate in a single county (Glenn). In instances where camps operated in the same geographic location, I addressed the risk of double counting by creating clusters.

Fire Camp	Location of Fire	Log Acres per Person
Trinity	Trinity, Shasta, and Siskiyou	3.61
Deadwood Camp	Siskiyou	3.6
Ishi Camp	Tehama, Glenn, Shasta and Plumas	3.3
Growlersburg	El Dorado	3.22
Puerta La Cruz	San Diego, Imperial and Riverside	3.2
Intermountain / Sugar Pine	Shasta	2.98
Mt. Bullion	Mariposa, Merced, and Madera	2.87
Rainbow / McCain Valley	San Diego	2.49
Devils Garden	Modoc	2.45
Antelope	Lassen Modoc	2.45
Fenner	Los Angeles, Kern and San Bernardino	2.32
Mountain Home	Tulare and Kern	2.27
Chamberlain Creek / Parlin Fork	Mendocino County	2.12
Bautista	Riverside and San Bernadino	1.95
Delta	Sonoma, Lake, Napa and Solano	1.9

Table 3.2.1: High Fire Camps, and Acres Burned Per Inmate (2014)

For example, two camps operating exclusively in San Diego County were grouped together and treated as a single entry, as shown in Table 3.2.1. After matching the acres burned to each camp or cluster, I calculated the acres burned per inmate by dividing the total acres burned for

each camp or cluster by the number of inmates. I then determined the median acres burned per inmate and used it to classify the population into two distinct groups: high fire and low fire exposure. This resulted in 15 camps being classified as high fire and 15 as low fire per year.

There are alternative methods for categorizing fire camps into high and low fire severity groups. Dividing them based on the median, as done in this analysis, does not account for the expected acres burned per county. Ideally, each county would have an established baseline of expected acres burned per year. This would then allow me to use the shocks in acres burned to determine if a fire camp participant was exposed to high or low acres burned. By analyzing these shocks, I could more accurately assess the impact of fire severity on participants. While the available fire data primarily spans from 2014 to 2024, I located data from 2013 and used it to construct a baseline for calculating “shocked” fire exposure. Specifically, I define shocked acres as the deviation from 2013 fire levels, which provides a consistent reference point across camps. I acknowledge that relying on a single year risks overfitting to anomalies, as fire activity can vary significantly from year to year. However, in the absence of multi-year pre-2014 data, the 2013 baseline offers the most feasible and transparent option for capturing relative shocks. To address this limitation, I run a separate specification using log shocked acres per person as the main regressor. This allows me to test whether deviations from typical fire activity, rather than absolute levels, meaningfully predict recommitment, offering a robustness check on the underlying relationship between fire intensity and post-release outcomes. The full distribution of shocked acres is provided in Appendix 2.

4. Results

In this section, I present the results of 3 logistic regressions and one exact matching model, as outlined in the methodology section. I begin with a logistic regression that uses recommitment

as the dependent variable and includes high fire as the primary independent variable. Additional controls are added sequentially: gender, race, sentence length, education, industry experience, job training, program participation, and self-help engagement. In the initial model, high fire is not statistically significant at any level, though the negative sign aligns with the hypothesized direction of the effect. To account for potential variation across years, I also estimated year-by-year regressions, as well as a pooled model using the full sample (Table 4.1). Complete yearly results are provided in Appendix 3.

Something worth noting in this regression, as well as those that follow, is the consistent significance of gender and race. Across all models, women and non-white individuals appear less likely to recommit. However, these results should be interpreted with caution. Women make up a relatively small portion of the sample, which may lead to less precise or more volatile estimates. Conversely, the large proportion of non-white individuals in the sample could inflate the statistical power of that coefficient, making even small differences appear highly significant. To address this, I disaggregate race into Black, Hispanic, Other, and White categories and separate results by gender. These breakdowns are presented in Appendix 4.

Table 4.1: Logistic Regression Predicting Recommitment (Mean DV = 0.112)

	Model 1	Model 2	Model 3	Model 4	Model 5
High Fire	-0.1595 (0.1232)	-0.1595 (0.1232)	-0.1574 (0.1238)	-0.1578 (0.1260)	-0.1592 (0.1194)
Woman		-0.7704*** (0.0003)	-0.7997*** (0.0121)	-0.8142*** (0.0126)	-0.8224*** (0.0371)
Non-White			-0.1605** (0.0639)	-0.1679*** (0.0633)	-0.1632*** (0.0627)
Sentence Length				-0.0036** (0.0017)	-0.0041** (0.0019)
Education (0/1)					-0.0810 (0.0733)
Industry (0/1)					0.0049 (0.3310)
Job (0/1)					-0.2945*** (0.0862)
Program (0/1)					-0.1597 (0.1572)
Self-Help (0/1)					-0.1292* (0.0693)
Constant	-2.1275*** (.02911)	-2.1275*** (.02911)	-1.9965*** (0.0626)	-1.8206*** (0.1007)	-1.4349* (0.1360)
Observations	11,399	11,399	11,399	11,399	11,399
Pseudo R ²	0.0133	0.0133	0.0141	0.0146	0.0181
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Job participation is significant across all regression models, suggesting a strong and consistent association between institutional work and reduced recommitment. This is in line with Bushway's (2003) summary of a meta-analysis showing a 20% lower recidivism rate among prison labor participants. While selection effects may influence these outcomes, the continuance of statistical significance in my models indicates that even lower-skilled institutional roles, such as mess hall, custodial, or grounds duties, may contribute positively to post-release outcomes. Holding all else constant, holding a job during incarceration is associated with a 29.45% decrease

in the log-odds of recommitment. To simplify the interpretation, I exponentiate the coefficient from Model 5 to obtain the odds ratio:

$$\exp(-0.2945) \approx 0.745$$

This implies that individuals who held a job during incarceration had approximately 25.5% lower odds of recommitting compared to those who did not ($1 - 0.745$).

Given the insignificance of the binary high fire variable, I turn to a continuous measure of fire exposure: log acres burned per person. This specification allows for greater variation in fire intensity across camps and individuals. The logistic regression framework and control variables remain the same, the only change is the substitution of the key regressor.

Table 4.2: Logistic Regression Predicting Reccommitment (Mean DV = 0.112)

	Model 1	Model 2	Model 3	Model 4	Model 5
Log Acres Burned Per Person	-0.1180** (0.0594)	-0.1180** (0.0594)	-0.1154* (0.0594)	-0.1215** (0.0579)	-0.1151** (0.0579)
Woman		-0.7638*** (0.0036)	-0.7930*** (0.0125)	-0.8079*** (0.0377)	-0.8158*** (0.0377)
Non-White			-0.1579** (0.0634)	-0.1657** (0.0626)	-0.1610** (0.0626)
Sentence Length				-0.0038** (0.0019)	-0.0044** (0.0019)
Education (0/1)					-0.0800 (0.0739)
Industry (0/1)					0.0109 (0.3318)
Job (0/1)					-0.2939*** (0.0863)
Program (0/1)					-0.1594 (0.1566)
Self-Help (0/1)					-0.1222* (0.0694)
Constant	-1.9838*** (0.0918)	-1.9838*** (0.0918)	-1.8583*** (0.1075)	-1.6604*** (0.1352)	-1.2902*** (0.1407)
Observations	11,399	11,399	11,399	11,399	11,399
Pseudo R ²	0.0137	0.0137	0.0144	0.0184	0.0184
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Log acres burned per person is statistically significant by itself and in the fully controlled specification, suggesting a robust negative relationship with recommitment. This aligns with my hypothesis: holding all else constant, a one-unit increase in log acres per person is associated with an 11.5% decrease in the log-odds of recommitting. For simplifying interpretation, doubling fire exposure per person corresponds to an increase of $\log(2) \approx 0.693$ units. Multiplying this by the coefficient yields $-0.1151 \times 0.693 \approx -0.0797$, and exponentiating gives $e^{-0.0797} \approx 0.923$ — indicating that doubling fire exposure is associated with approximately a 7.7% reduction in the odds of recommitment. Given that the baseline rate of recommitment is only 11.2%, even a small shift in odds can positively affect post-release outcomes.

To further normalize fire exposure, I examine how deviations from typical fire activity, measured as shocks relative to a baseline year, affect recommitment outcomes. Specifically, I use 2013 as the reference year to construct a variable for shocked acres burned per person, which serves as the main regressor in this specification. The logistic regression framework and control variables remain consistent with the previous models.

Table 4.3: Logistic Regression Predicting Reccommitment (Mean DV = 0.112)

	Model 1	Model 2	Model 3	Model 4	Model 5
Log Shocked Acres Per Person	-0.0561 (0.0402)	-0.0561 (0.0402)	-0.0563 (0.0403)	-0.0563 (0.0398)	-0.0847* (0.0447)
Woman		-0.7706*** (0.0003)	-0.8002*** (0.0120)	-0.8145*** (0.0126)	-0.8248*** (0.0371)
Non-White			-0.1620** (0.0637)	-0.1693*** (0.0631)	-0.1646*** (0.0624)
Sentence Length				-0.0036** (0.0017)	-0.0041** (0.0019)
Education (0/1)					-0.0823 (0.0733)
Industry (0/1)					0.0129 (0.3311)
Job (0/1)					-0.3025*** (0.0871)
Program (0/1)					-0.1637 (0.1574)
Self-Help (0/1)					-0.1319* (0.0684)
Constant	-1.6917*** (0.3407)	-1.6917*** (0.3407)	-1.5579*** (0.3529)	-1.3826*** (0.3636)	-0.7468* (0.4299)
Observations	11,399	11,399	11,399	11,399	11,399
Pseudo R ²	0.0129	0.0129	0.0137	0.0142	0.0179
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

The results show that log shocked acres per person becomes statistically significant at the 10% level only when all control variables are included in the model. A one-unit increase in log shocked fire exposure per person is associated with an 8.47% decrease in the log-odds of recommitting, simplified; doubling fire exposure relative to the 2013 baseline corresponds to a 5.7% reduction in the odds of recommitment, holding all else constant.

Running logistic regressions imposes a specific functional form on the data, requiring structural assumptions about how fire exposure affects recommitment. These assumptions may be overly restrictive or incorrect. To relax these parametric constraints and strengthen the causal interpretation, I employed exact matching. Individuals in high-fire camps were matched with

counterparts in low-fire camps who were identical across key characteristics: controlling offense, race, sentence length, education, industry, job, self-help participation, and program involvement. The only difference between matched individuals was their exposure to fire severity, with high-fire camps classified as the top half of log acres burned per person per year and low-fire camps as the bottom half. My goal was to leverage this direct comparison method to better isolate the impact of fire severity on recommitment outcomes.

To align with best practices for exact matching, I began with individuals in the high fire group (treatment) and matched each to all individuals in the low fire group (control) who shared identical covariates, excluding recommitment outcomes. This allowed for one-to-many matching, where a single treated individual could be matched to multiple control individuals. As a result, the final matched dataset included 15,494 observations. The primary difference observed was in recommitments: 2,052 in the high fire group versus 2,407 in the low fire group, leading to a 2.29 percentage point difference in recommitment, suggesting a possible association between fire classification and recidivism. However, since this analysis relies on exact matching, unobserved differences between individuals could still influence the results. Additionally, matching may introduce selection effects; for example, individuals who participate in industry or rehabilitative programs may already be more motivated to avoid recommitment, independent of the program's impact.

To see if the observed differences in recommitment rates between high fire and low fire groups were statistically significant, I conducted a test for differences in proportions. For each matching method, I calculated the probability of recommitment in both groups and used a standard error formula for independent proportions:

$$SE = \sqrt{\frac{p_1(1 - p_1)}{n_1} + \frac{p_2(1 - p_2)}{n_2}}$$

where p_1 and p_2 are the observed proportions of recommitment in the high fire and low fire groups, and n_1 and n_2 are their respective sample sizes. The Z-score was then computed as:

$$Z = \frac{p_1 - p_2}{SE}$$

Across all matching strategies (exact and relaxed), the differences in recommitment rates were statistically significant at the 1% level or better. For example, in the exact matching approach, recommitment rates were 13.24% in the high fire group and 15.54% in the low fire group, a 2.29 percentage point difference ($Z \approx -5.61$, $p < 0.001$).

To increase my sample size, I allowed for one variable to differ to create near-perfect matches. Initially, I considered letting this variable be random, but I recognized that some variables, like gender, may have a different impact than others, such as controlling offense. As a result, I first allowed race to differ while keeping all other variables constant. I then expanded the approach by allowing both gender and race to differ. Finally, I tested a more flexible matching strategy where only controlling offense and sentence length remained exact matches, allowing all other variables to vary.

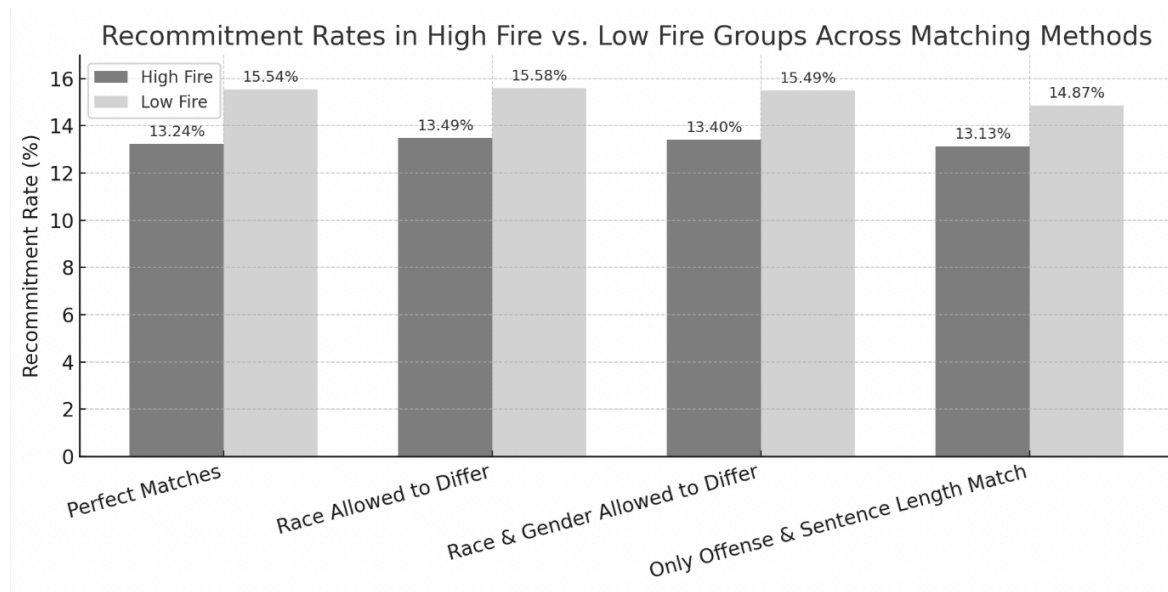


Table 4.4: Matching Methods Differences in Recommitments Between High and Low Fire Camps

As the matching criteria became more relaxed, the population size increased substantially. An observable difference in recommitments between the high-fire and low-fire groups emerged as the model became less restrictive. When allowing race to differ, the population size increased to 48,320 observations, revealing a 2.09 percentage point difference in recommitments, showing fewer recommitments in the high-fire group. Expanding the criteria to allow both race and gender to differ increased the population size to 58,046, with the difference remaining at 2.09 percentage points. Finally, when only matching on controlling offense and sentence length, factors I considered more influential in recommitments, the population size increased to 290,740, but the difference dropped to only 1.74 percentage points. This suggests that recommitment rates are around 2 percentage points lower for the high fire camp locations regardless of race, gender, or sentence length and offense.

Wanting to test whether demographic composition rather than fire exposure was driving variation in outcomes, I used ANOVA to examine how much of the variation in the percentage of

non-white individuals and women was explained by differences between camps versus differences within camps over time. As predicted the results for gender composition showed that 97.3% of the variation in the percentage of women was explained by differences between camps, with no variation within camps over time. This was expected as there are no co-ed fire camps. Race make-up showed a more balanced pattern: about 51% of the variation in the percentage of non-white individuals was between camps, and 49% was within camps across years. This balance implies that racial composition is not completely determined by camp structure, even though some camps are consistently more or less racially diverse. Rather, it also changes over time, potentially due to administrative decisions or broader intake patterns. The presence of substantial within-camp variation reduces concerns that fire exposure and race are fully intertwined. In other words, because racial composition shifts both across and within camps over time, it is less likely that the effects of fire exposure on recommitment are simply capturing differences in race. This strengthens the validity of fire classification as an independent factor, rather than as a proxy for demographic patterns. The variation in fire exposure, measured by acres burned, was impacted more by year to year changes rather than fixed camp differences. ANOVA results showed that 37.5% of the variation in acres burned was between camps, while 62.5% was within camps over time. This suggests that even though some camps may experience more fire activity than others on average, a large portion of fire exposure is determined by outside, time-varying factors such as weather, climate, or regional fire seasons. As a result, fire exposure is less tied to structural features of the camp and more influenced by changing environmental factors.

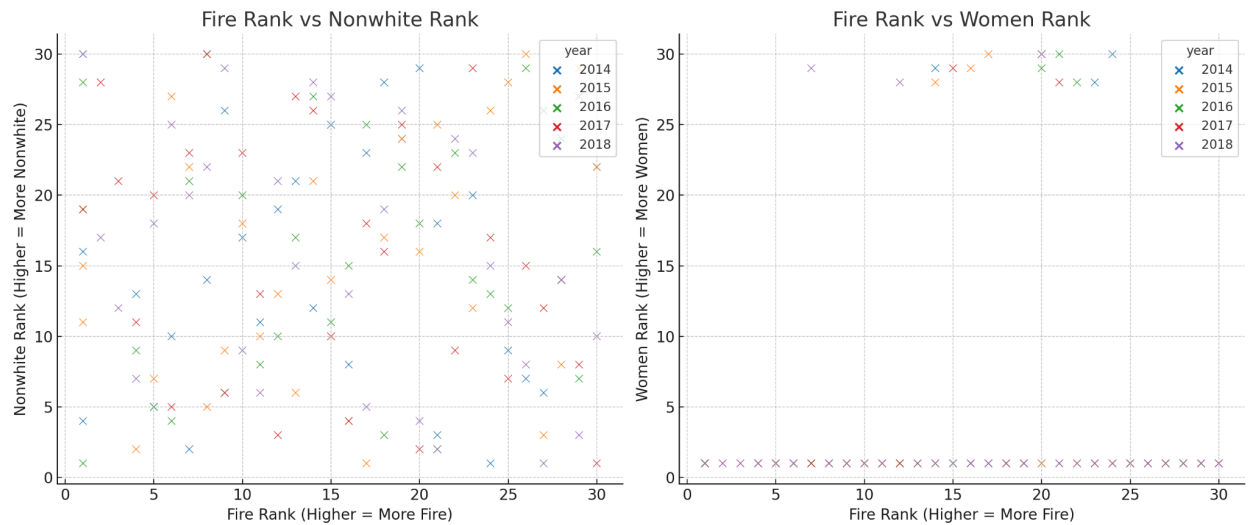


Figure 4.1: Fire Rank vs. Nonwhite and Female Population Rank by Camp-Year

Note: Each point represents a single camp in a given year. Camps are ranked from 1 to 30 based on three separate variables: total acres burned (fire rank), proportion non-white (nonwhite rank), and proportion female (women rank), with higher values indicating higher rankings. The left scatter plot compares fire rank to nonwhite rank, while the right compares fire rank to women rank. Colors indicate the year of observation.

I wanted to see if there was any correlation between high fire camp placement and non-whites or women so I decided to rank each camp by acres burned each year and compare those rankings to the rankings of camps by racial and gender composition. If high-fire camps systematically aligned with camps that had higher percentages of non-white or female individuals, that would raise the possibility of an alternative explanation influencing both fire exposure and recommitment. However, the rankings showed no consistent correlation: camps ranked high in fire exposure did not consistently rank high (or low) in non-white or female population percentages. This provides further support that fire exposure is not a proxy for demographic sorting, and helps single out fire classification as a more independent treatment

variable. In turn, this strengthens the central hypothesis that fire severity independently influences recommitment outcomes within the fire camp context.

5. Conclusion/Discussion

Taken together, the logistic regressions, matching methods, and supplemental models in the appendix provide strong evidence of a causal link between fire exposure and recommitment. This opens the door to two possible interpretations.

The first interpretation is to take the results at face value: individuals in fire camps with greater fire exposure have lower odds of recommitting, even after controlling for demographic characteristics and program participation. This pattern is supported by both the logistic regression findings and the lower observed recommitment rates in the matched sample analysis.

This likely reflects the division of labor within fire camps, those exposed to more fire activity are engaging in active firefighting, while those in low-exposure camps are assigned more grade work. This distinction follows Goodman's (2012) study, which found that incarcerated individuals consistently described firefighting as purposeful and esteem-building, while grade work was seen as physically demanding but largely demeaning. The results suggest that it may not be labor itself that matters, but the type of labor, specifically, whether it fosters self-worth and a sense of value, contribution, and purpose. This challenges the longstanding carceral focus on instilling "work ethic" as a rehabilitative tool. As Maguire, Flanagan, and Thornberry (1988) found, prison industry programs aimed at skill-building and discipline had no statistically significant impact on recidivism once selection effects were accounted for. Similarly, the higher recommitment rates in low-fire camps may reflect the limitations of labor framed purely around discipline, rather than purpose.

Viewing the results from this lens suggests that the goal should not be to simply expand fire camp programs, but to design interventions that focus on building self-esteem and instill a sense of purpose. This is consistent with Gendreau et al. (1979), who found that self-esteem at the end of incarceration was a strong predictor of recidivism ($R = 0.63$), and that higher self-worth was linked to better post-release adjustment. The implication is clear: rehabilitative efforts that meaningfully improve how individuals view their own value are more likely to yield long-term reductions in reoffending.

An alternative interpretation of my results centers on data limitations. Because the dataset only captures individuals who recommit and return to a fire camp, it excludes those who may have reoffended but return to walled prisons. This means that the observed lower recommitment rates in high-fire camps may not reflect true differences in recidivism. It's possible that individuals from high-fire camps are still recommitting, perhaps even at higher rates than those from low-fire camps, but are deciding to not go to fire camps after participating in a camp that had more fire exposure. This would suggest a deterrent effect rather than a rehabilitative one. Goodman (2012) found that 42.2% of incarcerated individuals described firefighting as dangerous and labor-intensive, reinforcing the idea that high fire exposure may discourage repeat participation in fire camps, even if overall reoffending remains unchanged.

However the literature from Goodman (2012), Gendreau et al. (1979), and Maguire, Flanagan, and Thornberry (1988) along with the results from the logistic regressions and matching method lean toward the first interpretation: that meaningful, purpose-driven labor like firefighting may reduce recommitment. Still, further research is needed using more comprehensive datasets that can capture all post-release outcomes, including recommitments to walled prisons, and control for additional variables such as age, education, and employment status upon release.

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Appendix 1: Linear Regression Models Using Alternative Measures of Fire Exposure

This appendix presents the full results of linear regression models estimating the relationship between fire exposure and recommitment. Three different specifications are used:

- Table A uses a binary indicator for high fire exposure
- Table B replaces the binary with a continuous measure: log acres burned per person
- Table C uses log shocked acres burned per person, calculated by comparing county-level fire exposure against a 2013 baseline

Table A: Linear Regression Predicting Reccommitment (Mean DV = 0.112)

	Model 1	Model 2	Model 3	Model 4	Model 5
High Fire	-0.0154 (0.0117)	-0.0154 (0.0117)	-0.0152 (0.0118)	-0.0152 (0.0120)	-0.0152 (0.0114)
Woman		-0.0524*** (0.0007)	-0.0552*** (0.0012)	-0.0566*** (0.0012)	-0.0574*** (0.0032)
Non-White			-0.0162** (0.0066)	-0.0169** (0.0066)	-0.0164** (0.0065)
Sentence Length				-0.0004** (0.0002)	-0.0004** (0.0002)
Education (0/1)					-0.0079 (0.0072)
Industry (0/1)					0.0015 (0.0251)
Job (0/1)					-0.0327*** (0.0101)
Program (0/1)					-0.0127 (0.0125)
Self-Help (0/1)					-0.0120* (0.0064)
Constant	0.1068 (0.0031)	0.1068 (0.0031)	0.1201 (0.0066)	0.1376 (0.0102)	0.1792 (0.0151)
Observations	11,400	11,400	11,400	11,400	11,400
R ²	0.0087	0.0087	0.0092	0.0096	0.0121
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table B: Linear Regression Predicting Recommitment (Mean DV = 0.112)

	Model 1	Model 2	Model 3	Model 4	Model 5
Log Acres Per Person	-0.012** (0.0059)	-0.012** (0.0059)	-0.0117* (0.0059)	-0.0123** (0.006)	-0.0116* (0.0058)
Woman		-0.0517*** (0.0004)	-0.0545*** (0.0012)	-0.056*** (0.0013)	-0.0567*** (0.0032)
Non-White			-0.0159** (0.0066)	-0.0167** (0.0066)	-0.0162** (0.0065)
Sentence Length				-0.0004** (0.0002)	-0.0004** (0.0002)
Education (0/1)					-0.0072 (0.0072)
Industry (0/1)					0.0021 (0.0252)
Job (0/1)					-0.0326*** (0.0102)
Program (0/1)					-0.0128 (0.0124)
Self-Help (0/1)					-0.0112* (0.0064)
Constant	0.1215*** (0.0091)	0.1215*** (0.0091)	0.1342*** (0.0108)	0.1539*** (0.0134)	0.1938*** (0.0153)
Observations	11,400	11,400	11,400	11,400	11,400
R-squared	0.0090	0.0090	0.0095	0.0100	0.0124
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C: Linear Regression Predicting Recommitment (Mean DV = .112)

	Model 1	Model 2	Model 3	Model 4	Model 5
Log Shocked Acres Per Person	-0.0058 (0.0046)	-0.0058 (0.0046)	-0.0058 (0.0046)	-0.0058 (0.0045)	-0.0086* (0.0051)
Woman		-0.0524*** (0.0004)	-0.0552*** (0.0012)	-0.0567*** (0.0012)	-0.0575*** (0.0032)
Non-White			-0.0163** (0.0066)	-0.0171** (0.0066)	-0.0165** (0.0065)
Sentence Length				-0.0004** (0.0002)	-0.0004** (0.0002)
Education (0/1)					-0.0080 (0.0071)
Industry (0/1)					0.0019 (0.0251)
Job (0/1)					-0.0336*** (0.0102)
Program (0/1)					-0.0131 (0.0125)
Self-Help (0/1)					-0.0121* (0.0063)
Constant	0.1519*** (0.0388)	0.1519*** (0.0388)	0.1656*** (0.0401)	0.1828*** (0.0409)	0.2494*** (0.0491)
Observations	11,400	11,400	11,400	11,400	11,400
R ²	0.0084	0.0084	0.0090	0.0094	0.0120
Camp FE	Y	Y	Y	Y	Y

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Appendix 2: Distribution Of Log Shocked Acres Per Person

A: Variable Construction

To capture relative fire exposure rather than absolute levels, I construct a variable for shocked acres per person as follows:

- First, I calculate each camp-year's deviation from its own 2013 fire exposure baseline:

$$\text{Shocked Acres} = \text{Acres Burned}_{ct} - \text{Acres Burned}_{c,2013}$$

- I then normalize this by dividing by the incarcerated population of the camp-year:

$$\text{Shocked Acres Per Person} = \frac{\text{Shocked Acres}}{\text{Population}_{ct}}$$

- Because the resulting values can be negative, I shift the entire distribution upward by subtracting the minimum value and adding one:

$$\text{Log Shocked Acres Per Person} = \log (\text{Shocked Acres Per Person} - \min + 1)$$

This transformation ensures all values are positive and log-transformable, providing a normalized measure of relative fire deviation across camps and years.

B: Summary Statistics (Log Shocked Acres Per Person)

Statistic	Value
Observations	11,400
Mean	8.402
Std. Dev.	0.664
Min	0.000
Max	9.049
Skewness	-9.803
Kurtosis	120.132

Appendix 3: Year-by-Year Logistic Regression Models Using Alternative Measures of Fire

Exposure

This appendix presents the full results of year-by-year logistic regression models estimating the relationship between fire exposure and recommitment. Three different specifications are used, each reported separately across the years 2014 to 2018:

- Table A uses the binary indicator for high fire exposure
- Table B uses log acres burned per person
- Table C uses log shocked acres burned per person

Table A: Logistic Regression Predicting Recombitment by Year (No Camp Fixed Effects)

	2014	2015	2016	2017	2018
High Fire	-0.0201 (0.1797)	-0.2986** (0.1363)	-0.2480 (0.1551)	0.1065 (0.1474)	0.0846 (0.1278)
Woman	-0.8288*** (0.2084)	-0.9328*** (0.3582)	-0.6740*** (0.1903)	-1.1337*** (0.3630)	-1.1048** (0.3408)
Non-white	-0.2777 (0.1516)	0.0695 (0.1380)	-0.3174** (0.1558)	-0.2677 (0.1395)	-0.0470 (0.1756)
Sentence Length	-0.0082*** (0.0030)	-0.0079*** (0.0028)	-0.0083 (0.0049)	-0.0091 (0.0051)	0.0019 (0.0065)
Education (0/1)	-0.0128 (0.1776)	-0.0885 (0.1095)	0.0621 (0.1417)	0.2068 (0.1703)	-0.2208 (0.1671)
Industry (0/1)	omitted	0.2132 (0.5194)	0.4628 (0.5558)	-0.1126 (0.7118)	-0.3292 (1.0221)
Job (0/1)	-0.1718 (0.0969)	-0.2114 (0.1510)	0.4478 (0.4942)	0.5604 (0.4200)	-0.4469 (0.2613)
Program (0/1)	0.2044 (0.3054)	-0.6561 (0.3772)	-0.0328 (0.3709)	0.0613 (0.2915)	-0.3002 (0.3531)
Self-help (0/1)	-0.1495 (0.1633)	-0.1537 (0.1725)	-0.0728 (0.1298)	-0.0723 (0.1666)	-0.0341 (0.1279)
Constant	-0.9223*** (0.2740)	-1.1664*** (0.2375)	-1.6422*** (0.4571)	-2.2831*** (0.4374)	-1.8508** (0.4004)
Observations	1,988	2,707	1,966	2,345	2,385
Pseudo R²	0.0104	0.0188	0.0122	0.0168	0.0133
Mean Recombitment Rate	0.155	0.117	0.122	0.091	0.085

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table B: Logistic Regression Predicting Reccommitment by Year (No Camp Fixed Effects)

	2014	2015	2016	2017	2018
Log Acres Per Person	-0.0250 (0.0801)	-0.1237 (0.0821)	-0.0742 (0.0790)	0.0213 (0.0643)	0.0863 (0.0784)
Woman	-0.8159*** (0.2116)	-0.9122*** (0.3442)	-0.7139*** (0.2207)	-1.1193*** (0.3801)	-1.0597*** (0.2962)
Non-white	-0.2779* (0.1513)	0.0674 (0.1393)	-0.3141** (0.1559)	-0.2685 (0.1386)	-0.1555 (0.1689)
Sentence Length	-0.0082*** (0.0031)	-0.0080*** (0.0028)	-0.0080* (0.0049)	-0.0092 (0.0057)	-0.0074 (0.0061)
Education (0/1)	-0.0126 (0.1774)	-0.0869 (0.1087)	0.0635 (0.1425)	0.2016 (0.1705)	-0.0753 (0.1550)
Industry (0/1)	omitted	0.2244 (0.5267)	0.4421 (0.5625)	-0.1116 (0.7118)	-0.1914 (0.9864)
Job (0/1)	-0.1711* (0.0974)	-0.2090 (0.1523)	-0.4406 (0.4950)	0.5610 (0.4200)	-0.2937 (0.2740)
Program (0/1)	0.2026 (0.3057)	-0.6603* (0.3812)	-0.0102 (0.3754)	0.0564 (0.2925)	-0.2820 (0.3346)
Self-help (0/1)	-0.1502 (0.1615)	-0.1526 (0.1701)	-0.0777 (0.1279)	-0.0734 (0.1674)	-0.0793 (0.1445)
Constant	-0.8914*** (0.3133)	-1.1273*** (0.2599)	-1.6289*** (0.4502)	-2.2612*** (0.4267)	-1.7536*** (0.3916)
Observations	1,988	2,707	1,966	2,345	2,385
Pseudo R²	0.0105	0.0179	0.0109	0.0165	0.0171
Mean Reccommitment Rate	0.155	0.117	0.122	0.091	0.085

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C: Logistic Regression Predicting Recommitment by Year (No Camp Fixed Effects)

	2014	2015	2016	2017	2018
Log Shocked Acres Person	0.2613 (0.2092)	-0.4725*** (0.0932)	0.0034 (0.0204)	0.1650*** (0.0600)	0.0087 (0.2160)
Woman	-0.7831*** (0.2454)	-0.8959*** (0.3318)	-0.7512*** (0.2133)	-1.1107*** (0.3795)	-1.1091*** (0.3421)
Non-white	-0.2803 (0.1507)	0.0610 (0.1379)	-0.3203** (0.1562)	-0.2651 (0.1399)	-0.0532 (0.1706)
Sentence Length	-0.0081*** (0.0030)	-0.0077*** (0.0028)	-0.0080 (0.0049)	-0.0093 (0.0057)	0.0019 (0.0065)
Education (0/1)	0.0021 (0.1766)	-0.0901 (0.1128)	0.0623 (0.1434)	0.2055 (0.1711)	-0.2192 (0.1666)
Industry (0/1)	omitted	0.1554 (0.5160)	0.4422 (0.5639)	-0.1153 (0.7134)	-0.3414 (1.0235)
Job (0/1)	-0.1884 (0.0968)	-0.1938 (0.1495)	0.4440 (0.4936)	0.5635 (0.4197)	-0.4500 (0.2624)
Program (0/1)	-0.2388 (0.3057)	-0.7357** (0.3572)	0.0095 (0.3846)	0.0657 (0.2916)	-0.3026 (0.3524)
Self-help (0/1)	-0.1297 (0.1611)	-0.2319 (0.1567)	-0.1057 (0.1337)	-0.0649 (0.1659)	-0.0356 (0.1303)
Constant	3.1395 (1.8602)	2.6735*** (0.7731)	-1.7694*** (0.5148)	-3.6212*** (0.5857)	-1.8836 (1.9492)
Observations	1,988	2,707	1,966	2,345	2,385
Pseudo R²	0.0111	0.0214	0.0102	0.0170	0.0130
Mean Recommit Rate	0.155	0.117	0.122	0.091	0.085

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Appendix 4:Recommitment Models Disaggregated by Gender and Race

This appendix provides logistic regression results disaggregated by key demographic groups to assess whether the relationship between fire exposure and recommitment varies meaningfully across subpopulations. These regressions build on patterns observed in the main models, where both gender and race consistently emerge as significant predictors of recommitment.

To investigate these patterns further, I run a series of subgroup regressions:

- Table A: presents regressions estimated on a sample that excludes women
- Table B: includes regressions estimated on women only
- Tables C/D/E: disaggregates race into 3 categories: Black, Hispanic, and White with separate regressions run for each group.
 - Shocked acres per person is omitted for the Black and Hispanic models due to data constraints. The shocked fire exposure dataset was built using a binary race variable and does not retain specific racial identifiers, making subgroup separation infeasible.

Table A: Logistic Regressions Using Alternative Measures of Fire Exposure With Male Population Only (DV mean = 0.118)

	High Fire	Log Acres Per Person	Shocked Log Acres Per Person
Fire Exposure	-0.1798 (0.1239)	-0.1195** (0.0585)	-0.0837* (0.0436)
Non-white	-0.1741*** (0.0654)	-0.1719*** (0.0653)	-0.1758*** (0.0650)
Sentence Length	-0.0039** (0.0020)	-0.0041** (0.0019)	-0.0039** (0.0020)
Education (0/1)	-0.1116 (0.0742)	-0.1099 (0.0750)	-0.1132 (0.0742)
Industry (0/1)	-0.3933 (0.4203)	-0.3871 (0.4204)	-0.3790 (0.4224)
Job (0/1)	-0.2869*** (0.0884)	-0.2861*** (0.0866)	-0.2948*** (0.0895)
Program (0/1)	-0.2319 (0.1586)	-0.2293 (0.1590)	-0.2349 (0.1582)
Self-help (0/1)	-0.0965 (0.0691)	-0.0902 (0.0691)	-0.1001 (0.0680)
Constant	-1.4355*** (0.1405)	-1.2882*** (0.1430)	-0.7600 (0.4246)
Observations	10,376	10,376	10,376
Pseudo R²	0.0124	0.0127	0.0120

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table B: Logistic Regression Predicting Recommitment, Female Only Sample
(DV Mean = 0.0499)

	Classification	Log Acres	Shocked Log Acres
Fire Exposure	0.3054 (0.2542)	0.2483 (0.6409)	-1.7231*** (0.2060)
Non-white	0.1556 (0.0851)	0.1592 (0.0822)	0.1475** (0.0724)
Sentence Length	-0.0075 (0.0110)	-0.0072 (0.0110)	-0.0085 (0.0109)
Education (0/1)	0.6570** (0.3078)	0.6661** (0.3026)	0.6455** (0.2811)
Industry (0/1)	0.8719*** (0.2864)	0.8533** (0.3452)	0.9371*** (0.2584)
Job (0/1)	-0.4748*** (0.0621)	-0.4560*** (0.0893)	-0.4608*** (0.0729)
Program (0/1)	0.3015 (0.5407)	0.3317 (0.4896)	0.3001 (0.5527)
Self-help (0/1)	-0.7963*** (0.1586)	-0.8474*** (0.1368)	-0.7999*** (0.1303)
Constant	-2.8681*** (0.2883)	-3.1908*** (1.1087)	11.8381*** (1.8705)
Observations	1,023	1,023	1,023
Pseudo R²	0.0370	0.0368	0.0391

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C: Logistic Regression Models Predicting Recommitment (White Only
Sample, DV mean = 0.1219)

	(1) High Fire	(2) Log Acres	(3) Log Shocked Acres
Fire Exposure	-0.2805 (0.1817)	-0.0668 (0.0912)	0.0050 (0.0449)
Woman	0.2874*** (0.0603)	0.2815*** (0.0609)	0.2805*** (0.0613)
Sentence Length	-0.0029 (0.0034)	-0.0030 (0.0034)	-0.0028 (0.0034)
Education	-0.0581 (0.1071)	-0.0569 (0.1080)	-0.0578 (0.1084)
Industry	-0.4651 (0.6082)	-0.4646 (0.6083)	-0.4700 (0.6073)
Job	-0.1859 (0.1500)	-0.1822 (0.1508)	-0.1818 (0.1507)
Program	0.0566 (0.2909)	0.0621 (0.2905)	0.0588 (0.2908)
Self-help	-0.0551 (0.1151)	-0.0540 (0.1177)	-0.0588 (0.1170)
Constant	-2.7625*** (0.2467)	-2.7156*** (0.2738)	-2.8726*** (0.4722)
Observations	3,265	3,265	3,265
Pseudo R²	0.0318	0.0306	0.0303

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table D: Logistic Regression on Recommitment (Black Subgroup Only)

	High Fire	Log Acres
Fire Exposure	-0.1507 (0.1839)	-0.0778 (0.0936)
Woman	-2.5561*** (0.1163)	-2.5388*** (0.1130)
Sentence Length	-0.0049 (0.0035)	-0.0050 (0.0035)
Education (0/1)	-0.0312 (0.1258)	-0.0273 (0.1256)
Industry (0/1)	-0.1137 (0.7072)	-0.1060 (0.7053)
Job (0/1)	-0.2568 (0.1667)	-0.2599 (0.1668)
Program (0/1)	-0.1413 (0.2878)	-0.1362 (0.2880)
Self-help (0/1)	0.1312 (0.1470)	0.1332 (0.1469)
Constant	-0.8649*** (0.2536)	-0.7844*** (0.2959)
Observations	2,278	2,278
Pseudo R²	0.0343	0.0343
DV Mean	0.123	

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Regressions include camp fixed effects clustered at the camp level.

Table E: Logistic Regression on Recommitment (Hispanic Subgroup Only)

	High Fire	Log Acres
Fire Exposure	-0.1022 (0.1158)	-0.1444** (0.0638)
Woman	-1.1826*** (0.0528)	-1.1700*** (0.0559)
Sentence Length	-0.0051** (0.0026)	-0.0054** (0.0025)
Education (0/1)	-0.1119 (0.1183)	-0.1100 (0.1192)
Industry (0/1)	0.3186 (0.6055)	0.3274 (0.6086)
Job (0/1)	-0.2198 (0.1470)	-0.2172 (0.1458)
Program (0/1)	-0.5809** (0.2885)	-0.5908** (0.2887)
Self-help (0/1)	-0.2594* (0.1423)	-0.2490 (0.1443)
Constant	-1.5328*** (0.1795)	-1.3331*** (0.1890)
Observations	4,561	4,561
Pseudo R²	0.0297	0.0307
DV Mean	0.101	

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Regressions include camp fixed effects clustered at the camp level.