

UNIVERSITY OF CALIFORNIA

Santa Barbara

Rebuilding a Community:

Residential Development Trends in the Aftermath of California Wildfires

By

Gabriel E. Etaat

A senior thesis submitted for the degree of

Bachelor of Arts

in

Environmental Studies

Thesis Advisor:

Dr. Robert Heilmayr, Assistant Professor, Environmental Studies Program

May, 2020

ABSTRACT

Rebuilding a Community:
Residential Development Trends in the Aftermath of California Wildfires
by

Gabriel E. Etaat

16 of California's 20 most destructive wildfires occurred between 1998 and 2018. As the climate crisis stimulates increasingly frequent, large-scale fires, the state's housing market exhibits signs of susceptibility to such short-term disturbances. To date, limited research has explored the process of rebuilding housing stock in the wake of wildfires. This process spans across the decision for homeowners to rebuild, the permit approval processes of local planning division offices, and the finalized reestablishment of these structures. A two-way fixed effects regression analysis of residential development permit issuance patterns was employed over a 21-year period to understand when communities exhibit signs of recovery, with a focus on housing permits issued in the seven years following a destructive wildfire across all 58 California counties. The results of the primary regression model failed to support any evidence of significant increases to local housing permits issued as an isolated impact of wildfires in the immediate years following. However, strong indicators exist for significantly increased permitting activities between four and seven years following these events. Upon further look, the per capita income bracket of a given county did not indicate significant differences in their ability to increase approval rates in any of the subsequent years, while the structure type composition of approved housing indicated no increases to housing density in affected regions. Given these factors, policies that subsidize or expedite the process of rebuilding housing after a wildfire are recommended if the intention of the policy is to speed up rehousing, but warnings are provided due to the existence of high-wildfire risk residential zoning throughout the state.

Acknowledgements

First and foremost, I'd like to thank my thesis adviser, Professor Robert Heilmayr, for guiding me every step of the way. If not for his stimulating counterarguments, peer-reviewed recommendations, and ever-so-gentle reminders to stick with the timeline, I would not have been able to accomplish a paper worth priding over.

I would also like to extend my gratitude to Professor Simone Pulver, who has provided me with an overwhelming amount of guidance and support throughout this process. Her genuine enthusiasm for the thesis program cannot be exaggerated, as the dozens of the students she has previously, currently, and, most certainly, will continue to advise exhibit her incredible advising through their work. For encouraging me to partake in a senior thesis and contributing to the educational influences that drew me to this topic, I'd like to thank Professors Olivier Deschenes, Peter Rupert, and David Cleveland. I'd also like to acknowledge Katie Maynard, who inspires me every day to work towards a greener and more equitable future.

Lastly, I'd like to thank everyone who provided emotional support and feedback at any point during this journey. This include my relatives—Shahrokh, Elias, and Dorothy—as well as friends and peers—Kevin Nguyen, Miranda O'Brien, Siena Matsumoto, and the 2020 senior thesis class of the Environmental Studies Program.

Table of Contents

Note Regarding External Files.....	ix
Chapter 1: Introduction.....	1
1.1 Research Question.....	1
1.2 Research Relevance.....	1
1.2.1 Policy Contribution.....	2
1.2.2 Academic Contribution.....	3
1.3 Assumptions and Hypothesis.....	3
1.3.1 Assumptions and Terminology.....	3
1.3.2 Hypotheses 1-4.....	6
1.4 Research Design.....	8
1.5 Thesis Roadmap.....	8
Chapter 2: Literature Review.....	10
2.1 Introduction.....	10
2.2 Wildfires and Housing in California.....	10
2.2.1 Climate Change and Wildfires.....	11
2.2.2 History of Wildfires in California.....	12
2.2.3 California Housing Market.....	12
2.3 Community Wildfire Rebuilding Efforts.....	12
2.3.1 Rehousing Timeline Analysis.....	13
2.3.2 Policy and Perceptions of Wildfire Risks.....	14
2.3.3 Socioeconomic and Demographic Indicators.....	15
2.3.4 Suggested Models of Recovery.....	15
2.4 Conclusion.....	17
Chapter 3: Background.....	18
3.1 Wildfire Concepts and Government Interventions.....	18
3.1.1 Wildland Urban Interface.....	18
3.1.2 The California Landscape.....	19
3.1.3 Housing Related Wildfire Government Interventions.....	19
3.2 Building Permit Approvals in California.....	20
3.2.1 Typical Housing Approval Timelines.....	21
3.2.2 CEQA Implications for California Permitting Process.....	22
3.3 Wildfire Trends.....	23
3.4 Community Implications of Wildfires.....	24
3.4.1 Homeowner Insurance.....	24
3.4.2 Public Health.....	26
3.4.3 Electricity Access.....	27
Chapter 4: Methodology & Data Collection.....	28
4.1 Two-way Fixed Effects Regression Model.....	28
4.2 Data Sources.....	30
4.2.1 Existing Housing Data.....	30

4.2.2 <i>Building Permits Issued Data</i>	31
4.2.3 <i>Income and Population Data</i>	31
4.2.4 <i>Fire Data</i>	32
4.3 <i>Data Wrangling and Merging</i>	33
4.4 <i>Initial Observations and Summary Statistics</i>	34
4.4.1 <i>California Housing Permit Trends</i>	34
4.4.2 <i>Housing and Population</i>	36
4.4.3 <i>“Fire” County Permitting Trends</i>	37
4.4.4 <i>Comparing the Treatment and Control Groups</i>	39
Chapter 5: Regression Analysis	41
5.1 <i>Primary Regression Model Inputs</i>	41
5.2 <i>Primary Regression Model Results</i>	44
5.2.1 <i>Per Capita Income as a Correlated Factor</i>	45
5.2.2 <i>Years 1 Through 3 Post-Fire</i>	45
5.2.3 <i>Years 4 Through 7 Post-Fire</i>	46
5.3 <i>Alternative Approaches and Errors</i>	46
5.3.1 <i>“Lead” Years</i>	47
5.3.2 <i>Single-Family vs. Multi-Family Permitting Comparison</i>	49
5.3.3 <i>12 Year Approach</i>	51
5.4 <i>Averaged Scenario for the Application of Coefficients</i>	53
Chapter 6: Conclusion	56
6.1 <i>Testing Hypothesis 1-4</i>	56
6.2 <i>Research Limitations</i>	57
6.3 <i>Academic and Policy Recommendations</i>	58
References	61

Note Regarding External Files

Included in the following paper is a written description, analysis and discussion of the datasets and statistical processes utilized to complete this research. However, files pertaining to the raw data and coded procedures exist beyond this single document. The datasets and R Scripts which produced the tables, graphs, and metrics for this research can be accessed at the following repository location. For detailed procedures as to how the data was sourced and formatted, please view the read_me file and comments made throughout the R Script thesis_data.r

https://github.com/Gabriel-Etaat/senior_thesis.git

Chapter 1: Introduction

1.1 Research Question

Throughout California, homeowners face a terrible fear - will their home be the next to go up in flames in the path of yet another wildfire? More than 350,000 residents of the state live in regions categorized as “Very High” risk wildfire hazard zones, and as both the quantity and severity of these fires increases over time, many communities will be unprepared to face the destruction to come (Dixon et al., 2018). However, while wildfire homeowner risks become easier to predict, the reactions and rebuilding efforts of victims are largely unknown. In an attempt to contribute to the growing pool of research in this field, this paper quantifies when rebuilding efforts take place by California communities in the aftermath of destructive wildfires, with a focus on isolated impacts to the issuance of residential building permits following these instances. A regression analysis of housing, wildfires, and other county-level characteristics provides insight on changes to permit approval trends to determine if communities begin to significantly rebuild homes during these post-fire years across differences in time, region, and per capita income levels.

1.2 Research Relevance

Although thousands of studies and reports regarding wildfire destruction have been authored, there is no clear roadmap for homeowners, local planning division officials, and policy makers to employ when strategizing rebuilding efforts post-disaster. Many considerations go into the decision to rebuild, relocate locally, or emigrate entirely to a new region, such as the availability of rehousing grants, transitional housing,

expedited permit approvals, homeowner income, and more (Mockrin et al., 2016). Particularly for homeowners residing in Wildland-Urban Interface (WUI) zones, redeveloping may pose unbearable costs in the form of maintained wildfire risks and increased homeowner insurance rates (CNRA, 2018). Furthermore, few papers have analyzed the observed housing impacts of wildfires in particular, due in part to inconsistent data collection and publication processes. How these factors interact with each other, and which ones have a significant impact on how and when homes are rebuilt, is unknown both within California and globally. Here, insight is provided to encourage thoughtful and sustainable rebuilding guidelines for collaborators invested in this process.

1.2.1 Policy Contribution

With regards to government policy efforts, two contrary factors should be considered when determining its role in a community's recovery process: the effectiveness of a policy in aiding rapid rehousing, as well as the risks associated with exemptions or costs made for those redevelopments. On one hand, California officials in local planning and development departments are already incentivized to increase the number of approved residential housing permits issued as a result of the state's housing crisis. Some restrictions, although time-consuming, are necessary to prevent the erection of dangerous or risky structures, such as the California Environmental Quality Act (CA Department of Fish and Wildlife, 2020). However, especially in times of crisis, increased incentives for residential construction in the form of expedited approvals and exemptions from months-long processes, such community input hearings, may be warranted under the right conditions. Although the lagged effects associated with the time it takes between a homeowner's decision to rebuild to the actual construction of approved permits are

assumed constant in the research analysis, this factor may be a notable roadblock in the path of a community's recovery.

1.2.2 Academic Contribution

Among academics, fire rebuilding efforts have had limited analysis, with even fewer conclusions made regarding the “when” consideration of this topic. Most publications on wildfire impacts in California are primarily qualitative in nature, with limited data on more contextual factors such as the counts of houses destroyed and rebuilt from wildfires (Abrams et al., 2015). Perhaps the most prominent scholarly contribution of this study is the creation of a wildfire impacts dataset which, based on the county reports, newspapers articles, and existing database fragments of various sources, summarizes the structural damage of 26 major wildfires in California over the course of 21 years. With this data, the regression analysis employed by combining this data with existing databases shines light on the fixed effects fires, with other considerations such as wealth, have on housing in light of existing confounding housing patterns. By addressing this concept, scholars can adapt this database for further modelling, and take the results of this analysis to further understand the natural and social relationships between these various factors.

1.3 Assumptions and Hypotheses

1.3.1 Assumptions and Terminology

Several key assumptions were made prior to employing the analysis of this research, based on the prior research and current topics discussed in Chapters 2 and 3. In absence of an existing wildfire impacts database, the validity of the sources and the use of

total (commercial & residential) structures destroyed in the fire database is assumed to accurately reflect a consistent measure of relative impact on housing across all regions (discussed further in Chapter 4). By analyzing regions at the county level, an assumption is made that statistically significant impacts to county permitting trends would be proportionately reflective of what happens in the distinct communities impacted in absence of spatial data to map specific regions. With regards to the regression setup and outcomes, it is also assumed that independent variable coefficients reflect a causal relationship, and that enough fire data exists to accurately estimate up to seven years of future impacts from the wildfires on permitting practices, to be discussed later.

Throughout this paper, the terms “housing permits” and “building permits” are brought up frequently and with interchangeable meaning. Although not all building permits are residential-specific, the structures destroyed and rebuilt by wildfires are presumed to be primarily residential, thus the term is used due to the narrowed use of housing-specific building permits in the research methods section.

1.3.2 Hypotheses 1-4

Table 1: Hypothesis Test Terms		
Variable/Subscript	Meaning	Coefficient Indicator
total_mf_sf_perm	The total number of single family and multifamily housing permits issued	-
total_sf_perm	The total number of single family housing permits issued	-
total_mf_perm	The total number of multifamily housing permits issued	-
struc_dest	The number of structures destroyed by an observed wildfire	X
over_40	A binary variable indicating whether an observation has a per capita income above \$40,000	Z
struc_dest*over_40	An interaction term denoting the explanatory relationship between these two variables	W
c	Indicator for the region of an observation, divided across the 58 distinct counties of California	-
t	Indicator for the time of an observation, divided across the 21 years between 1998-2018. A value of “T” here represents an observation when a wildfire occurs	-

The following four hypotheses, each pertaining to the outcomes of the regression models, can be interpreted using the descriptions in Table 1. First, in the primary regression model, it is predicted that statistically significant, positive impacts for each structure destroyed will be apparent in the five years following a wildfire instance:

$$\mathbf{H^1_A: X_{c,t=T+1} \& X_{c,t=T+2} \& \dots \& X_{c,t=T+5} > 0}$$

Within this same model, the binary variable `over_40` is used primarily as an interaction term to indicate X coefficients are amplified in higher per capita income counties . With respect to these interaction terms, it is hypothesized that in the first two follow-up years, there will be a statistically significant, positive impact for the respective coefficients, indicating that counties in years where per capita income is above \$40,000 will experience a larger increase in building permits issued during this period than those which do not.

$$\mathbf{H^2_A: W_{c,t=T+1} \& W_{c,t=T+2} > 0}$$

For the last hypothesis of this model, it is anticipated that the increase to approved housing permits will peak at 3 years following a wildfire for counties in the higher per capita income bracket, while 5 years will be the peak for those not in the lower bracket. These values are based on the idea that regions in counties with more resources will recover faster due to larger homeowner incomes and government aid dollars to encourage rebuilding efforts, as well as the findings of related studies (Alexandre et al., 2014):

$$\mathbf{H^3_A: X_{c,t=T+3} + W_{c,t=T+3} > \text{any } X_{c,t} + W_{c,t} \text{ where } t \neq 3 \text{ AND}}$$

$$\mathbf{X_{c,t=T+5} > \text{any } X_{c,t} \text{ where } t \neq 5}$$

Several variations of the primary model are tested to ensure the results and interpretations of the original model are valid. Among those is a change to the independent variable, `total_mf_sf_perm`, in two new scenarios where single family and multifamily housing permits are separated out into two distinct dependent variables. In accordance with the assumption that the total structures destroyed as opposed to units destroyed by wildfires is a valid proxy due to the dominance of single family residence zoning regulations typically associated with the WUI regions wildfires are most prominent in, we expect the model with `total_sf_perm` to render statistically significant results similar to the original model, while the model with `total_mf_perm` to not exhibit such significant values.

H⁴_A: $X_{c,t}$ for $T < t < T+6$ significant IF $Y = \text{total_sf_perm}$ AND

$X_{c,t}$ for $T < t < T+6$ NOT significant IF $Y = \text{total_mf_perm}$

1.4 Research Design

By grouping all variables in the finalized dataset to be grouped by county and year, a two-way fixed effects regression model is employed. All continuous patterns from year-to-year and across all counties are assumed to be made endogenous with this approach, thus isolating the effects of unpredictable region-and-time specific wildfire destruction. County data, as opposed to spatial data specific to the precise region of a given fire, was chosen due to its comparability, functionality within the model type, and availability of widespread county-specific databases. The time period, 1998-2018, was chosen in order to accommodate a large number of wildfire observations with ample

observation years following the wildfire instance during as recent a period as possible. By choosing a recent time period at the time of evaluation, data was more readily available, and as climate change continues to increase the frequency at which highly destructive fires occur, this also happened to encompass the largest number of fires of this magnitude within a 21-year period.

Five distinct datasets were combined for both general aggregate analysis and the regression models. One of these datasets, `fire_df`, is a compilation of 26 unique fire or fire complexes with significant structural damage across 25 unique county-year pairings. All known wildfires that have occurred in the state of California and destroyed at least 120 structures during the observation period were included in this database. A variety of online sources, including newspapers and government agencies, provides information that was manually input to the master dataframe regarding structures damaged/destroyed and units damaged/destroyed. Prior to the analysis of the regression model, a series of tables, graphs, and metrics are generated from the merged data to provide insight on endogenous, yet relevant, housing trends throughout the state of California, general information pertaining to the 13 counties in the observation group, and more.

Further analysis of the data using analysis in R provides insight into the direct relationship discussed in the thesis statement. After manipulating existing variables to reflect growth rates, binary indicators, and other necessary values for analysis, the following primary regression model was employed:

$$\begin{aligned} \log(\text{total_mf_sf_perm}_{t,c}) = & B_0 + B_1 \text{lag}(\text{struc_dest}_{t,c}, 7) + B_2 \text{lag}(\text{struc_dest}_{t,c}, 6) + \dots + \\ & B_7 \text{lag}(\text{struc_dest}_{t,c}, 1) + B_8 \text{over_40}_{c,t} + B_9 \text{lag}(\text{struc_dest}_{t,c}, 7) * \text{over_40}_{c,t} + \\ & B_{10} \text{lag}(\text{struc_dest}_{t,c}, 6) * \text{over_40}_{c,t} + \dots + B_{11} \text{lag}(\text{struc_dest}_{t,c}, 1) * \text{over_40}_{c,t} + e \end{aligned}$$

Where $\text{lag}(\text{struc_dest}_{t,c}, 7)$ is representative of $\text{struc_dest}_{t=T+7,c}$ from the hypothesis tests. Statistical significance of the coefficients, as well as their signs and magnitudes, will serve as a general framework for assessment. The dependent variable, total_mf_sf_perm , is logged to provide proportionate values for single-value changes in the dependent variables.

After interpreting the values of these coefficients and applying them to general scenarios, further applications of the regression framework are applied with different variables and observation years. These variations are employed in order to confirm the validation of the results from the original model, as well as to explore other relationships relating to permit approval types and lagged yearly impacts beyond the framework of the original model.

1.5 Thesis Roadmap

In the following chapters, I explore residential development in the aftermath of wildfires, along with relevant factors to this discussion. In Chapter 2, supporting research and relevant publications in this field are reviewed to identify what existing research has to say regarding the factors and expected outcomes at work with this topic, with supporting literature in related fields such as climate change and geographic factors that promote wildfire frequency and intensity. Chapter 3 consists of a review of major wildfires observed, the major economic factors contributing to the California housing crisis, and other supportive information to better understand the implications and socioeconomic relevance of the research findings. Further information pertaining to the

research methodology, databases, and general findings incorporated into this study are detailed in Chapter 4, along with specific data sourcing instruction and R Scripts in the attached digital files. The primary regression model and its variations are depicted and analyzed in Chapter 5, followed by a broader discussion regarding the implications and possible flaws of the research in Chapter 6. In this concluding paragraph, the hypothesis and other connections to discussions of previous chapters are revisited with the finalized results factored in.

Chapter 2: Literature Review

2.1 Introduction

While research on the causes and instances of wildfires in the past few decades is consistent and well established, analysis regarding community recovery actions and timelines is not as thoroughly developed. After exploring the research bridging the relationship between climate change and wildfires, modern history of wildfires in California, and the state's housing market, specific publications in the field of wildfire recovery are reviewed for their data sourcing, methodologies, and conclusions. By drawing upon the insights, and gaps, of this research, a unique approach within this field is employed using the original fire dataset to expand on the findings of research observing wildfires with more restrictive data and quantitative approaches.

2.2 Wildfires and Housing in California

2.2.1 Climate Change and Wildfires

Throughout the history of California, wildfires have played a vital, yet destructive role for its residents and their properties. They have served as a critical component to many natural systems, such as their necessity to promote the germination of native vegetation in many regions across the state (Keeley, 1991). However, these healthy fires follow a predictable time trend, which has been pushed out of equilibrium in recent years. Studies as early as the 1980's have provided evidence correlating the increase of anthropogenic climate change to increased frequencies and ferocities of wildfires across the world by means of higher temperatures, decreased humidity, and overall variations affecting the natural ecosystems of the planet (Clark, 1988) . These correlations soon

became proven causal relationships as researchers identified a series of clear relationships between increased greenhouse gas emissions, droughts, vegetation patterns, and other factors (Westerling & Bryant, 2007; Abatzoglou & Williams, 2016).

2.2.2 History of Wildfires in California

During a time categorized by “suppression-period fires”, natural fires patterns affiliated with specific regions across the state began to take large numbers of lives where Californians had urbanized (Martin & Sapsis, 1995). Without the knowledge or infrastructure to plan for or around these occurrences, cities experienced unprecedented impacts. For example, 584 structures were destroyed by a single fire in Berkeley, California, in 1923, and another 117 homes were lost to a wildfire in 1929 in Mill Valley. These casualties began to subside as government officials adapted zoning regulations and vegetation management to subdue and redirect natural wildfire patterns. Since 1991, during the “urban interface and fire management” period, these tactics have become increasingly stringent as the severity and frequency of fires has increased, as well as the neglect of government entities to restrict development in wildland-urban interface (WUI) zones. The correlation between location and fire risk for housing has been well established, a relationship well documented in the southern California WUI regions predominantly occupied by fuel-rich chaparral plants (Syphard et al., 2012). One study of the southwestern United States found the number and average of wildfires over the past four decades have increased regardless of vegetation type, with significantly increasing trends in the severity of effect on both wildlife and development (Singleton et al., 2018).

2.2.3 California Housing Market

As dangerous a threat as wildfires can pose to aspects of a community, such as tourism revenue, air quality, and even mortality, real estate damages can easily impose some of the harshest financial and lifestyle challenges to those impacted. This is especially concerning in a state such as California, which has struggled to meet the housing needs of its residents in recent years due to a variety of factors. One comparative study with other states identified two characteristics of California contributing to this trend: stricter-than-usual residential construction requirements and state taxes that disincentivize residential development when compared to those imposed on commercial projects (Quigley & Raphael, 2005). These factors further magnified the impacts of Great Recession in 2008, when struggling homeowners had been susceptible to mortgage overreach in face of unaffordable housing (Bardhan & Walker, 2010). Models of future development vary vastly on regulatory predictions, but predictions for the regions and land mass of residential growth are fairly consistent, indicating that housing will continue to encroach on WUI zones throughout the state (Mann et al., 2014).

2.3 Community Wildfire Rebuilding Efforts

Limited research has been done on the aftermath of residential regions impacted by large wildfires. Homeowners must decide how, when, or even whether they should rebuild, while city planners and policy makers need to provide their services in order to facilitate the process. However, the actions being taken and their implications on the timing and characteristics of rehousing are scarcely documented through peer-reviewed publications.

2.3.1 Rehousing Timeline Analysis

At the core of modern rebuilding analysis is the characterization of the permitting trends for new homes in an affected region, as well as documenting external factors which contribute to this process such as government subsidy policies, community engagement, and homeowner perceptions. This approach was first employed on a national scale with the observation of all major US wildfires between 2000 and 2005 (Alexandre et al., 2014). After observing the year-to-year trends of damaged, destroyed, and newly developed residential structures, it was concluded that only 25% of burned homes were rebuilt within 5 years, and yet pre-fire developments number far fewer than the 5-year total inside fire perimeters. These results are not only comprehensive, but also align well with other studies, such as a case study of a 2010 fire in Colorado where only 30% of homes were rebuilt after three and a half years (Mockrin et al., 2015). After interviewing homeowners both impacted and unharmed by the fire, the researchers found that all homeowners were generally either unaware of wildfire risks, willing to face them despite this knowledge, and/or “economic incentives to rebuild in the same place outweigh[ed] perceived risk”. The results of this paper support the hypothesis that approved housing permits will significantly increase beyond the normal year-to-year trends immediately following a wildfire, although the magnitude of these effects may be weak.

In California, wildfire risk is sometimes incorporated into housing growth models, with those that focus on this as a primary indicator further reinforce the impact zoning away from WUI zones has as the strongest abatement strategy (Bryant & Westerling, 2014). However, this same study indicates that California zoning officials are generally

averse to this strategy, consistently encroaching further into these regions than those in the Sierra Nevada Foothills communities. This trend is believed to continue into the future due to the increased need for urban sprawl and other population density-residency relationships.

2.3.2 Policy and Perceptions of Wildfire Risks

Individual communities can provide clear case studies of the sociopolitical processes that determine the pace of rebuilding. One case study of regions in the Colorado Front Range affected by fires between 2010 and 2012 indicated that adaptation through rebuilding was underway, but both individuals and government were doing little to nothing to avoid redeveloping in WUI zones (Mockrin et al., 2016). Although permits issued were noted, this study favored a qualitative analysis by observing recovery policy and outcomes, along with interviews with policy makers, fire experts, and post-disaster homeowners. Results indicated an unwillingness for policy makers and homeowners to migrate or incentivize migration out of WUI zones, favoring practices such fire-resistant building materials and vegetation mitigation, despite a general consensus that these alternatives would probably not play a key role in protection from “extreme” fires.

A similar pattern has also been identified in California communities under a similar case-study methodology. A paper analyzing communities in Sonoma and Ventura Counties impacted by 2017 wildfires indicated that, while local governments in these WUI-prominent regions did take some planning and structural measures to abate development in high-risk regions, “actions taken after the fires primarily focus[ed] on rebuilding quickly”, primarily in the form of grants and subsidies to homeowners (Herrera, 2019). The adaptive, rezoning, or emigration incentive policies sometimes

explored in pre-fire years are even found to be discouraged due to a variety of pressures including existing federal aid agencies, homeowners, and the lack of strict rules pertaining to abatement practices. Although the exact degree to which these policies influenced rehousing behavior is not explored beyond the immediate aid, it is presumed that significant increases in building permit applications for these regions were intended to be generated by means of government intervention.

When weighing in the relative implications of different factors and individuals to rebuild a community, there appears to be disproportionate impacts. A study on rebuilding efforts from Nevada and New Mexico wildfires took an abstract analysis approach in “scale matching, linking within and across scales, and institutional flexibility” with regards to the various fires and communities observed. (Abrams et al., 2015). By breaking down the rebuilding efforts into these three categories, the researchers were able to identify key players, communication networks, and developmental proceedings surrounding each respective community, concluding that institutions and organizations played the most critical roles in facilitating adaptation and community resilience. Thus, more than ever, it is becoming evident that the immediate actions of local and state officials can, and will, have the most profound effect on the future of a community’s rebuilding efforts.

2.3.3 Socioeconomic and Demographic Indicators

Due to the increasing frequency of wildfires, studies are beginning to explore the socioeconomic correlations between communities impacted by wildfires. One such study created a model for community wildfire vulnerability by combining demographic, housing, language, education, and socioeconomic factors pertaining to specific regions

with adaptive capacity characteristics such as vegetation types, weather, historical fire occurrences, and more (Davies et al, 2018). The results indicated severe racial and socioeconomic differences in wildfire vulnerability, although susceptibility to increased frequency of wildfires could not be explained by these differences. One example of this trend was identified with the differences between the urban east San Francisco Bay region against the rural eastern Sierra Nevada Mountains of California; while both have similar wildfire potential, “the relatively poorer socioeconomic conditions in the Sierra Nevada Mountains make those communities far more vulnerable to fire disaster than their exurban counterpart.

2.3.4 Suggested Models of Recovery

Even as the actual research on this issue remains limited, models regarding best practices for community adaptation continue to develop, which often involve a combination of infrastructure and locational changes depending on the socioeconomic state of the region (Schumann et al., 2019). In the “hot moment” aftermath period, the researchers argue that reducing future vulnerability requires a combination of short-term rebuilding goals and long-term landscape alterations, yet no mention of rezoning laws or emigration are cited in this paper.

Efforts and resources needed to adapt are another consideration being made in designing these plans. One case study of eight different communities affected by wildfires found that local governments and organizations invest more into recovery and adaptation efforts in communities where wildfire is “novel and there is already government capacity and investments” in such regulations and planning departments (Mockrin et al., 2018). Furthermore, financial factors such as external funds and staff

capacity played a critical role in the level of investment made towards rebuilding efforts. Strategies utilized widely among the observed communities were hazard planning documents, emergency response protocols, and some type of suppression strategy, yet land use planning and regulations “remained largely unchanged”. Given these facts, the researchers conclude that local and state governments need to reconsider land use zoning as a tool against wildfire destruction, and call towards individuals to make conscious decisions when planning their own rebuilding journey.

2.4 Conclusion

Based on the methodologies, observations, and data restraints of previous studies, I have chosen to build upon the quantitative housing evaluations of former researchers utilizing different data sources and analysis models. Bearing in mind that only moderate rehousing developments are observed many years after wildfire occurrences in these studies, the focus of my analysis will incorporate the significance and proportionate impacts wildfires have on housing trends in each subsequent year. By observing a larger set of regions, time periods, and wildfires, errors in the form of broader generalizations may be observed. This underutilized regression approach to fix the effects of existing housing trends unveils new perspectives on the relationship wildfires have within the larger context of the California housing market while also analyzing the immediate regional effects exhibited on those directly impacted.

Chapter 3: Background

3.1 Wildfire Concepts and Government Interventions

3.1.1 Wildland Urban Interface

The Wildland Urban Interface, often referred to as the WUI, is a spatial categorization brought to life by observations made in the 2000 report, “A Report to the Council of Western State Foresters—Fire in the West—The Wildland/Urban Interface Fire Problem” (USFS, 2001). According to this federal report, the WUI “exists where humans and their development meet or intermix with wildland fuel.” This term was coined in order to implement the foundational criteria for risk assessment of individual communities, due to an observed fragility of those located at these noted borders. For the specific application of risk assessment, a structure is considered “either a residence or a business facility, including Federal, State, and local government facilities” and excludes “small improvements such as fences and wildlife watering devices” (USFS, 2001). Variations of this category have been normalized despite the existence of a federally-approved, tiered definition for qualifying regions.

Research on the relevance of the federal definition in predicting wildfire occurrence is supportive, but not entirely consistent. One study, which took into account California wildfires and traditionally categorized WUI regions, found that the typical housing density and proximity to wildlife factors may be missing a key component—vegetation type (Kramer et al., 2018). The California Fire Science Consortium, the group that authored this study, also identified the lack of the WUI to incorporate low-density structures as a flow in this tool, which are often widely affected by wildfires as well.

Due to this lack of consistency, along with limitations pertaining to the analysis of specific regions impacted by wildfires, a county-level approach was favored in my research despite the use of WUI groupings in other academics in this field.

3.1.2 The California Landscape

The California Montane Chaparral and Woodland ecoregion is a complex terrain of varying fire-adapted communities. Within this larger topographic categorization that defines the region observed in this study are the chaparral, mixed-conifer forests, alpine habitats and more (WFF, 2020). These regions vary in vegetation type, fuel loads, and wildfire relationships, but are generally understood to be a more resilient and tolerant terrain with respect to wildfires. Among the most dependent terrains for wildfires are the conifer forests, chaparral, and oak woodlands, which cover about 50% of the state (CWAM, n.d.)

Although most human development is located primarily at the bottom of valleys, where fire risks are lower and fuel loads are naturally lower, this feature of California's landscape has made communities especially vulnerable to natural disasters. Furthermore, the fragmentation of ecological regions by developmental divides accelerates the accumulation of dense fuel loads due to disruptive pathways for wildfire movement (WFF, 2020).

3.1.3 Housing Related Wildfire Policy Interventions

A variety of actions can be taken at the local, county, or state level to assist homeowners in recovering from a wildfire. According to the California Governor's Office of Emergency Services (Cal OES), a multitude of laws and executive orders could be enforced depending on the magnitude and implications of a given fire (Cal OES, n.d).

This includes, but is not limited to, equal housing protection during transitional periods, assistance on insurance claims, loans, emergency housing recovery funds, and more. However, with the exception of advising from department officials and emergency executive orders, assistance programs are largely deferred to local agencies by that state.

How and when local governments mobilize to help a community recover varies largely as well. Local governments often facilitate funds provided by agencies such as the U.S. Department of Agriculture (USDA), the U.S. Department of Housing and Urban Development (HUD), and the Federal Emergency Management Agency (FEMA) to provide loans, grants, and temporary housing based on factors such as the extent of damage incurred, the income of a homeowner, the housing type of the damaged structure, and more (Cal HCD). Debris removal, rehousing assistance, and educational materials are also commonly facilitated by local and county government officials, as listed on the City of Santa Rosa's website due to the onslaught of fires in Sonoma County in 2017 (City of Santa Rosa, n.d.). Across seven web pages visited relating to government actions to assist homeowners in the aftermath of wildfires, none described any policies related to the permanent relocation of residents to new regions.

3.2 Building Permit Approvals in California

Given that isolated variations in housing permits issued over time are analyzed in place of the exact number of destroyed wildfires that are rebuilt in this study, an understanding of the nature and applicability of this indicator is explored. On top of the usual permitting processes most local planning division offices follow across the nation, California faces increased regulations which add further requirements. Taking into

account common characteristics of the regions and housing structures impacted by the observed wildfires, an estimate regarding the lagged representation of this variable is made in understanding the time it takes homeowners to completely rebuild their homes.

3.2.1 Typical Housing Approval Timelines

Although each local and state district has the power to mandate additional requirements, with possible disaster-related exemptions, certain measures are standard across all planning division offices. The Federal Emergency Management Agency, an agency of the U.S. Department of Homeland Security, summarizes this “general” process for receiving building permit approvals with a toolkit intended, in part, for individuals who need to recover from a natural disaster (FEMA, 2020). The document describes how the following seven measures are typically necessary in some form for any individual, regardless of the reasoning or type of housing project: project planning, pre-application submission, formal application submission, permit review processing, permit issuance, on-site inspections, and final approval. Not all building permits issued are approved, nor do these structures follow a consistent timeline up until the finalized construction, but consistencies are apparent within the categorizations of these projects.

Although the initial phases of these projects are largely variant due to the conditions and timing needed for homeowners to identify developers and prepare for the many requirements to come, most single-family housing permits follow a similar trajectory during the application review period. Many local planning offices, such as the city of San Luis Obispo’s Planning Division Office, state that “minor” projects, such as the construction of single-family homes, are typically reviewed for their initial plans within four weeks, as opposed to eight weeks or more for applications pertaining to

commercial or large-scale projects (SLO, n.d.). Furthermore, planning offices typically allow no more than six months for minor housing projects to commence construction to avoid permit denial. The California Department of Housing and Community Development further echos these generalizations on their “Sample Analysis” report regarding their processing and permitting procedures page, adding that design review approvals typically take 2-6 weeks for single-family projects while larger projects can be expected to take 6-12 weeks (HCD, 2018).

According to data from the U.S. Census Bureau's 2017 Survey of Construction, Once a permit is issued, the average construction of a single-family home is about seven and a half months after construction commences (Gibson, 2018). Given the construction commencement timelines imposed upon issuance and this data, it is assumed in the discussion of the regression analysis that the actual reconstruction of a home can be expected to be completed in the year following the approval of its building permit. In absence of data indicating the proportion of building permits issued to permits approved upon completion, it is estimated that all housing permits issued as a result of the isolated effects from wildfires are constructed and approved given the expected urgency of these homeowners.

3.2.2 CEQA Implications for California Permitting Processes

The most unique aspect to rehousing efforts and timelines in the state of California is the additional requirements imposed by the California Environmental Quality Act (CEQA). Enacted in 1970 as a supplement to its federal equivalent, the National Environmental Policy Act (NEPA), in order to place more restrictions, reporting measures, and public input into the processing of building permits (CA Department of

Fish and Wildlife, 2020). For example, many project applicants must prepare Draft Environmental Impact Reports (DEIR) to be made public and open to rebuttal prior to approval. Although many developers, policymakers, and legislatures have called for a reform of the policy in recent years due to its “negative cost and timing impacts on market-rate and affordable housing production”, research from the 2018 Survey of California Cities & Counties indicates that Environmental Impact Reports and other timely impacts from this policy “are generally reserved for large projects” (Heimer & Hitchcock, 2019). Therefore, although other reporting and inspection requirements are certainly imposed on single family developments in California not experienced in other regions, it is assumed that the development project permits being issued as an effect of wildfires are not as heavily impacted by the regulations as large other, commonly larger projects.

3.3 Wildfire History and Trends

Ever since human development began encroaching on the natural cycles of California’s ecosystems, wildfire patterns have fluctuated. Prior to the historic Gold Rush which ushered in immigrants, there were an estimated 50 to 70 trees per acre throughout California’s forestlands (Kelly, 2018). As of 2018, that figure has jumped to more than 400 trees per acre. Combined with poor forest management practices, this population trend has put considerable pressure on the shrinking, undeveloped regions of California. Immigration of highly-developed communities began in 1848 with the start of the Gold Rush, which would usher in 300,000 residents within 7 years in a region which previously had about 2000 non-natives (Tikkanen, 2017). Between 1970 and 2018, the

population has doubled from 20 to 40 million residents, which has rooted itself in all sorts of socioeconomic issues such as urban sprawl, a housing crisis, and deforestation (Helvarg, 2019).

As a result of these trends, the intensity of wildfires is larger than ever. Between 1930 and 1998, only six California wildfires exceeded 100,000 acres in size (Berke & Varinsky, 2018). Since then, there have been nine. Government expenditures have also increased--California's Department of Forestry and Fire Protection spent about \$505 million fighting fires in 2017, in contrast the \$47 million the state spent in 1997.

As previously noted, residential development patterns depict worrisome fire risks. With about 7 million homes currently located in high or extremely high wildfire risk zones, there is over a 1,000% increase in such developments since 1940 (Barron & Gajanan, 2017).

3.4 Community Implications of Wildfires

Wildfires affect communities long after the event takes place, in forms ranging from insurance costs to public health to electricity access. Although the socioeconomic terrains of California communities are an essential consideration when predicting and observing recovery efforts, which will later be analyzed in Chapters 4 & 5, many general trends and statewide metrics have been identified.

3.4.1 Homeowner Insurance

Although most heavily experienced by individuals affected by wildfires in California, an increasing financial burden is being placed on at-risk homeowners by means of housing insurance. Homeowner insurance not only provides critical support to

victims of disasters, but also contribute to housing market patterns disincentivizing residency in high-risk zones through risk-based price portfolios (CNRA, 2018). However, rising prices can put overwhelming financial pressure on currently unaffected homeowners, which further explains the varied means wildfires have shaped community circumstances in California.

In California, there are three sources of coverage, each with varying assessments and backings (CNRA, 2018). Most homeowners opt to go through the admitted insurers market, which is thought to be the most reliable option due to California Insurance Guarantee Association (CIGA) protection. These insurers pay regular fees in the event that one becomes insolvent, which could help provide such an insurer's customers with up to \$500,000 in an emergency. Alternatively, homeowners can opt for the surplus lines market (or non-admitted market), which consists of insurers overseen in their state of central operations. The lack of CIGA backing and California rate regulation result in higher premium costs, since this is often a default for wealthy homeowners who require more specific coverage requirements, and are therefore turned down in the admitted market. Lastly, the California FAIR Plan, which was enacted in 1968 as an alternative to insurance programs, provides basic wildfire coverage for residential and commercial structures by pooling together the resources of admitted insurers on a needs-basis. However, this policy lacks common insured risks such as theft and liability. The policy was drastically expanded in 2016 to allow most homeowners to apply, not just those rejected by insurers.

Research indicates that wildfires are causing a decrease in admitted insurer agreements, increased insurer-initiated nonrenewals, and increased reliance on surplus

line markets and FAIR Plan policies (CNRA, 2018). As insurers update their risk portfolios, fewer homeowners are being admitted for insurance in high-risk regions, while surplus line premiums remain relatively stable. The California Department of Insurance, which must approve of increased deductible rates, has approved many rate changes over the past few. These decisions are primarily approved to maintain market stability--insurers lost about \$24 billion dollars due to the wildfires of 2017 and 2018. As overall homeowner insurers begin to exclude more residents, both through pricing and more stringent standards, the 98.3% of admitted market policy holders in 2014 are facing immense pressure to reconsider coverage options (CNRA, 2018).

3.4.2 Public Health

A growing area of concern as more communities are impacted by large-scale wildfires is public health from associated hazards. Particle pollution dispersed by the ash and smoke byproducts of wildfires has always caused respiratory and general health issues for surrounding communities, but research is indicating that the composition of these particles may be worse than previously observed (Gibbens, 2019). Recent fires have induced allergy-like symptoms to many individuals, while those more susceptible to respiratory issues have caused drastic increases in local emergency room admittances (CBS, 2019).

Although short-term air pollution affects may be limited to temporary discomfort and low mortality rates, concerns are being raised regarding the long-term health implications of these occurrences. One study of underage victims exposed to prolonged Air Quality Indexes well above a healthy limit found that their immune systems to be severely impaired compared to the control group, which may have been the result of

now-controversial fire abatement practices (Pruniki et al., 2019). Carcinogens, toxins, and metals have been found in surrounding communities of severe wildfires, and as more developments are destroyed over time, the physical, financial, and mental health of fire victims may become more severe as fires become more frequent and destructive.

3.4.3 Electricity Access

According to government evaluations, California wildfires incurred more than \$700 million in utility costs between 2000-2016 (CEC, 2018). Additionally, both wildfire-induced and planned power outages for precautionary purposes have resulted in energy-reliant health concerns, lowered business efficiency, and additional costs (Bliss, 2019). The states leading energy, PG&E filed bankruptcy due to liability lawsuits for igniting multiple fires, increasing maintenance costs to prevent future instances, and more complications related to the wildfire crisis (Lazo & Carlton, 2019).

Projections of wildfire damages to electricity grids and related structures are not projected to worsen from 2000-2016 levels, but are subject to the increased frequency and destructiveness of future fires (CEC, 2018). As a result, many plans have been proposed by government officials and private institutions, such as centralizing urban facilities, microgrid developments, and utility company bailouts. Particularly with regards to microgrid development, at-risk communities with electricity reliance on conventional grids stand to benefit from these projects in order to meet short-term energy needs.

Chapter 4: Methodology & Data Collection

4.1 Two-Way Fixed Effects Regression Model

While the intention of this research is to understand how housing growth changes in the aftermath of destructive wildfires, there are a vast number of different factors influencing these patterns, both related and unrelated to the wildfire itself. Population growth, urbanization, rezoning practices, development approval processes, and other considerations commonly observed in the California housing market also factor into changes to the rate at which housing permits are issued in these subsequent years. These same factors not only impact the change in annual rates of housing development, but also vary from county to county. Heterogeneities are presented by county-level differences across all time periods, and must be accounted for within a model when attempting to identify the distinct impacts of wildfires. For example, 200 structures destroyed in a low-density county could have a much more significant relative impact to its housing portfolio than the same damages imposed on a high-density county.

In order to control for all factors impacting housing permit issuing practices at a fixed rate across time or counties, a two-way fixed effects model is utilized in order to observe the only known year-and-county specific disruption to housing development patterns--large, destructive wildfires. Therefore, the input to our model is grouped by both the 58 California counties and the 21 years observed in this study, which enables county-specific intercepts to provide an insightful control group, and thus meaningful output for the independent variable coefficients. Year-to year trends proportionate across all counties, such as the Great Recession, do not obscure with the interpretation of the wildfire impacts. Likewise, proportionate differences between counties that are consistent

across time periods, such as the general demand for new housing quantities based on characteristics and densities of different regions, are also accounted for.

To further generate meaningful coefficient outputs, the dependent variable--the number of housing permits issued--is logged in this regression. Thus, the explanatory variables of the model can produce a relative indicator of change by region as opposed to more variant unit-to-unit relationships. In other words, the H_A^3 of this study indicates that the coefficient for $\text{struc_dest}_{t=T+3,c}$, which indicates the percent change on housing permits issued 3 years following a destructive wildfire for each structure destroyed under this setup, is a positive, statistically significant value between 0 and 1. These coefficient values signify a percent change to building permits issued as a result of a one-unit increase in an independent variable such that 0 indicates a 0% increase, 1 indicates a 100% increase, and -1 indicates a 100% decrease per unit.

$$\begin{aligned} \log(\text{total_mf_sf_perm}_{t,c}) = & B_0 + B_1 \text{lag}(\text{struc_dest}_{t,c}, 7) + B_2 \text{lag}(\text{struc_dest}_{t,c}, 6) + \dots + \\ & B_7 \text{lag}(\text{struc_dest}_{t,c}, 1) + B_8 \text{over_40}_{c,t} + B_9 \text{lag}(\text{struc_dest}_{t,c}, 7) * \text{over_40}_{c,t} + \\ & B_{10} \text{lag}(\text{struc_dest}_{t,c}, 6) * \text{over_40}_{c,t} + \dots + B_{11} \text{lag}(\text{struc_dest}_{t,c}, 1) * \text{over_40}_{c,t} + e \end{aligned}$$

In theory, this model should indicate the causal relationship between wildfire damages and housing permits issued, although unincorporated, non-regular factors could interfere with this assumption. A discussion of these estimates and possible flaws of the model can be found in Chapter 6.

4.3 Data Sources

Prior to establishing the 33 distinct variables of master_df, data was collected from a variety of public sources, government agencies, reports, and newspaper articles. For each database source, information is provided on who the agencies involved are, what collection and methodology procedures they followed to produce this data, and why this data is required for the analysis of this study. Details on how the data can be replicated from these sources into the format utilized for subsequent data cleaning and analysis can be found in the attached read_me file.

4.3.1 Existing Housing Data

Data regarding the existing housing units in a given county and year was accessed from the California State Association of Counties (CSAC). This non-profit organization serves to lobby, advocate, and generally represent all of the state's counties at the state and federal levels. CSAC provides all of the data from their "DataPile" database online to the public. Although the sources of this database derive from a variety of sources, the specific dataset utilized for this study, "Housing Units - Number of Single-Family, Multi-Family, and Mobile Homes by County - 1991 to 2018", is entirely sourced from the State of California Department of Finance. Data was utilized from this secondary-source because it is in a more compatible format, having already been grouped by both county and year. Although the methodology of how the data was altered to fit its new format is not explicitly clear, this government-funded organization is presumed to have followed standard guidelines to avoid alterations to the intended values. Furthermore, a representative from CSAC was contacted, and was able to confirm that the data was directly sourced and processed in an appropriate manner.

Existing housing, for both single family and multifamily units, was observed as a reference point for interpretations of housing permit growth rates and yearly, regional totals.

4.2.2 Home Building Permits Issued Data

Data regarding the number of housing permits issued in a given county and year was obtained from the State of the Cities Data Systems (SOCDS) database from the U.S. Department of Housing and Urban Development (HUD). According to this source, the database “contains data on permits for residential construction issued by about 21,000 jurisdictions collected in the Census Bureau's Building Permits Survey.” Data from this tool is displayed in a tabular format specific to the website’s interface, so it was subsequently copied and pasted into an Excel workbook to be uploaded as a csv file. Details regarding the data output measures and transfer are detailed in the attached read_me file.

Grouped distinctions for the number of building permits issued by county and year from the SOCDS database were used as the dependent variable in the core regression of this study. Variations of this value, separated by single-family and multifamily permit types, were used as inputs to the general model framework as well in order to test for H_A^4 .

4.2.3 Income and Population Data

In order to fix wealth as an indicator for a region’s ability to recover from wildfires, per capita income data was downloaded from the U.S. Bureau of Economic Analysis. As an agency of the Department of Commerce, this is a trusted data provider which sourced data from the Census Bureau for the CAINC1 database. Population,

income, and per capita income variables were obtained from this source. Per capita income is utilized as an indicator to control for the size of wildfire impacts on a given county, as well as a source for comparison when discussing relative impacts beyond the constraints of the regression model.

4.2.4 Fire Data

Table 2: Wildfire Destruction Dataset

	county	year	fire_name	county_code	struc_dest	struc_dam_dest
1	Amador	2,015	Butte Fire	6,005	877	921
2	Butte	2,008	Humboldt Fire	6,007	351	
3	Butte	2,017	Cherokee Fire, La Porte Fires	6,007	80	82
4	Butte	2,018	Camp Fire	6,007	18,804	
5	El Dorado	2,007	Angora Fire	6,017	309	
6	Lake	2,015	Valley Fire	6,033	1,955	2,048
7	Lake	2,017	Sulphur Fire	6,033	162	170
8	Lake	2,018	Mendocino Complex Fire	6,033	246	
9	Los Angeles	2,008	Sayre Fire	6,037	604	
10	Los Angeles	2,018	Woolsey Fire	6,037	1,121	1,310
11	Mendocino	2,017	Redwood Complex Fire	6,045	546	589
12	Napa	2,017	Atlas Fire	6,055	120	903
13	San Bernardino	1,999	Jones Fire	6,071	954	
14	San Bernardino	2,003	Old Fire	6,071	1,003	
15	San Bernardino	2,016	Blue Cut Fire	6,071	321	324
16	San Diego	2,003	Cedar Fire	6,073	2,830	
17	San Diego	2,007	Harris Fire, Witch Fire	6,073	2,198	
18	San Diego	2,017	Lilac Fire	6,073	157	221
19	Shasta	2,013	Clove Fire	6,089	201	211
20	Shasta	2,018	Carr Fire	6,089	1,614	1,675
21	Sonoma	2,017	Tubbs Fire, Central LNU Complex Fires	6,097	6,991	7,480
22	Ventura	2,003	Simi Fire	6,111	300	
23	Ventura	2,017	Thomas Fire	6,111	1,063	280
24	Ventura	2,018	Woolsey Fire	6,111	522	674
25	Yuba	2,017	North Bay Fires	6,115	264	274

At the core of this analysis is the observation of wildfires and the impact they impose on communities. In the initial phases of this researcher, a table listed on CAL FIRE's website provided a foundation for the number of structures destroyed by the most destructive wildfires ever recorded in California, although this data is severely limiting (CAL FIRE, 2019) . As depicted on Table __, data for 26 different fires that have

destroyed at least 120 structures between 1998-2018 were collected from various sources, including government webpages, county fire reports, and online news articles. Due to the constraints presented by the lack of a comprehensive wildfire destruction database or data collection procedure, possible inconsistencies in public reporting of damages, and ambiguity in the unit total of residency impacts by fire, are present. The constructed dataset primarily reflects the total number of buildings destroyed by a given wildfire, listed in the variable `struc_dest`. More specific distinctions relating to whether structures were classified as residential and those that were merely damaged were noted, but too many uncertainties were present to utilize this data in a meaningful way. URLs pertaining to the sources of all data points are listed under “source” in the original data file.

Rather than listing each fire as a unique observation, a variation of this table is grouped by county and year prior to uploading the data in order to maintain compatibility with the other datasets. Therefore, multiple counties could observe residential destruction from a single fire, thus further estimates and internet searches were needed in order to assign the number of structures destroyed by a fire to each distinct county. Likewise, a single county in a given year may have been subjected to destruction from multiple wildfires. Further information on the assumptions and flaws of this dataset can be found in Section 6, while detailed information on how the database was constructed can be found in the `read_me` file.

4.3 Data Wrangling and Merging

After collecting the data from these five unique sources, they were uploaded and cleaned in an R Script prior to the merging of the finalized, general dataset. The code

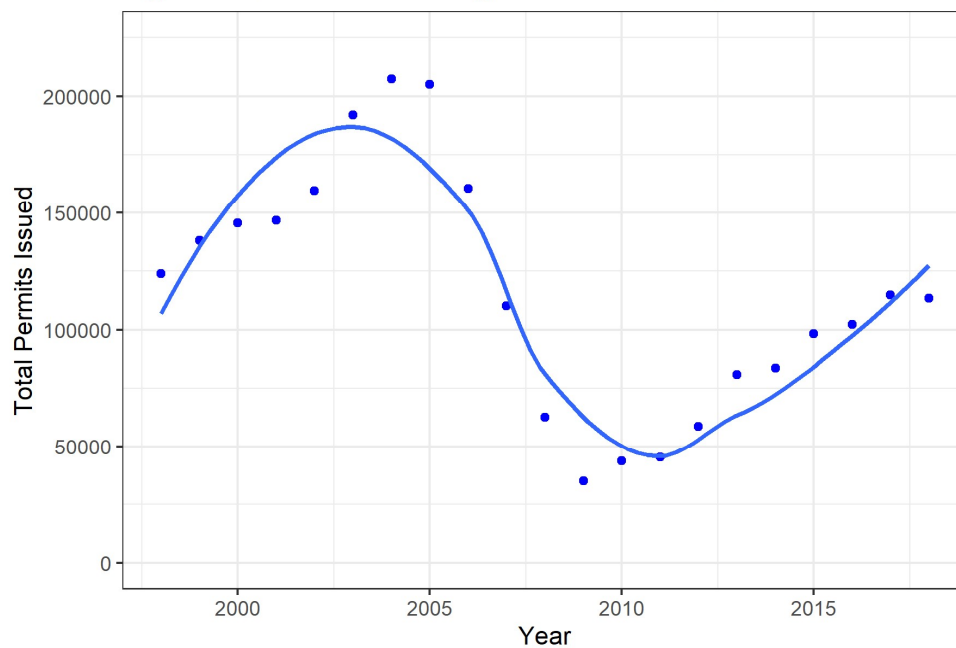
itself, with detailed notes for most operations throughout this process, can be found in the attached “thesis_data.R” file. A key component to this process was that all datasets had to be grouped by both county and time, with a 59th observation under the county column created to identify “California” totals for certain variables.

The final dataset, master_df, is a 1239 x 33 dataframe, with variables regarding existing housing, housing permits issued, demographics, and wildfire occurrences. 9 of these variables were created during the merging process to indicate growth rates pertaining to county-specific observations as well as binary indicators for wildfire occurrences. At the end of this data sorting, master_df is saved as a csv file to be uploaded into other R Scripts for analysis and visualization purposes.

4.4 Initial Observations and Summary Statistics

4.4.1 California Housing Permit Trends

Figure 1: California Housing Permits Issued Over Time



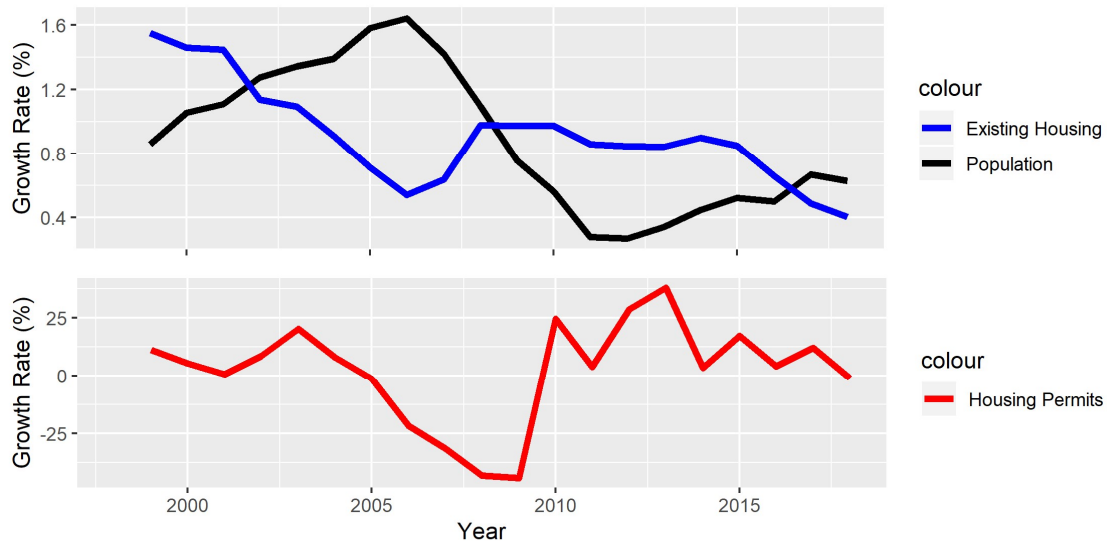
Source: U.S. Department of Housing and Urban Development

As depicted by Figure 1, California has seen inconsistent growth regarding the development of new housing structures. With a maximum of 207390 in 2004 and a minimum of 35069 just 5 years later, the impacts of housing unaffordability, mortgage overreach, and other related factors discussed in previous chapters took their toll on the demand for new housing during this time. However, permitting practices have been on the rise since this time as the statewide economy recovered and the risks affiliated with bad loans decreased.

When analyzing the impacts to permitting trends in the model employed for this research, year-to-year variations that are consistent across all 58 counties in California are omitted. Therefore, a national recession, and other factors which are constant across all regions, would not factor into the impacts captured by the regression model. However, it is important to consider both external and internal impacts to rehousing in a given region, especially given that a short term negative blow to housing during a time of negative housing permit growth could magnify the extent to which housing applications and approvals decrease in subsequent years

4.4.2 Housing and Population

Figure 2: California Population, Existing Housing, and Housing Permits Growth Rates Over Time



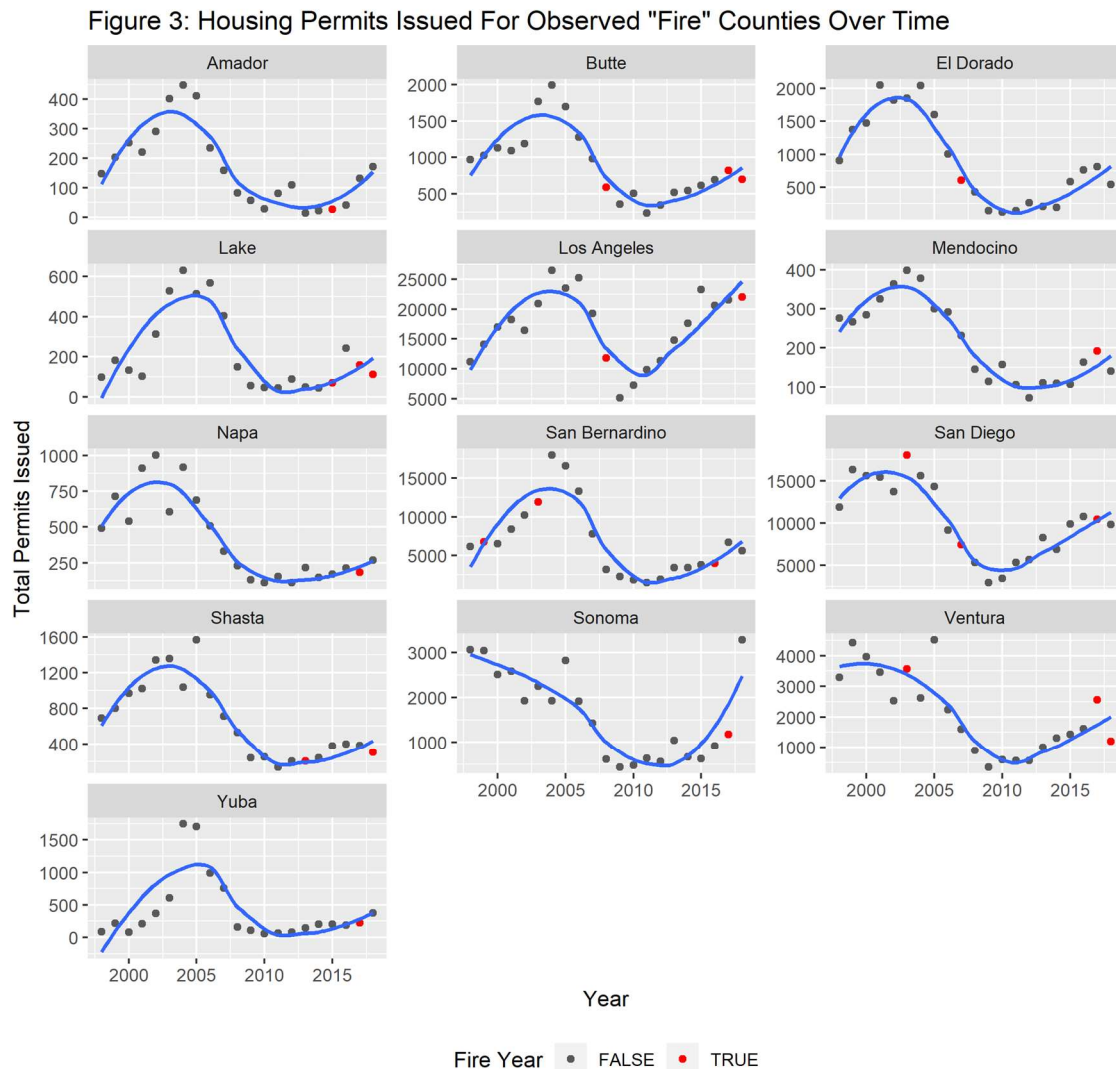
Sources: U.S. Department of Housing and Urban Development, California State Association of Counties & U.S. Bureau of Economic Analysis

Housing development is only as important as the number of individuals who need accommodations. In 2018, there were approximately 2.92 individuals for each housing unit in California as opposed to 2.89 individuals per unit in 1998. Although this may appear as a modest change, an analysis of year-to-year changes for these factors further help us understand how these fixed effects can leave regions within the state susceptible to short-term disruptions.

In Figure 2, year-to-year growth rates for population, existing housing, and housing permit approvals are compared across two grids for the general state of California. As with the previous graph, the trends depicted are both endogenous and held constant within the model of this research. However, it is important to consider how and when population growth exceeds housing growth throughout the state when considering widespread housing availability, as well comparing changes in permitting practices to as they relate to these time periods. Between 2008 and 2017, in the fallout of the Great

Recession, not only did the state’s population grow faster than available housing, but consistent growth was apparent with residential housing permits. This is not to say the population was suddenly booming--there is a lagged relationship between housing permits being issued and the actual completion of the project, which is a major consideration when discussing the timeframe in which rehousing occurs. Furthermore, depreciation of existing housing, high-density housing projects, and other factors may explain these variations in growth patterns.

4.4.3 “Fire” County Permitting Trends



Source: U.S. Department of Housing and Urban Development

Of the 58 counties in California, 13 were severely impacted by the fires in this study. Figure 3 depicts the same general trend depicted in Figure 1 for the state of California, but focuses on the county level with fire years indicated.

When comparing the permitting practices at the county level to the state level, most regions appear to follow a similar pattern. Larger counties, such as Los Angeles, appear to generally follow similar growth patterns due to decreased variability in numbers, although an effect in itself may be evident with the relationship between dense urban regions and greater need for increased housing permits issued. Nevertheless, it is apparent in every region that, just prior to the crash of the housing market, the frequency at which housing permits were being approved was decreasing, and these regions would see varying degrees of recovery in order to increase housing approvals over the following 10+ years.

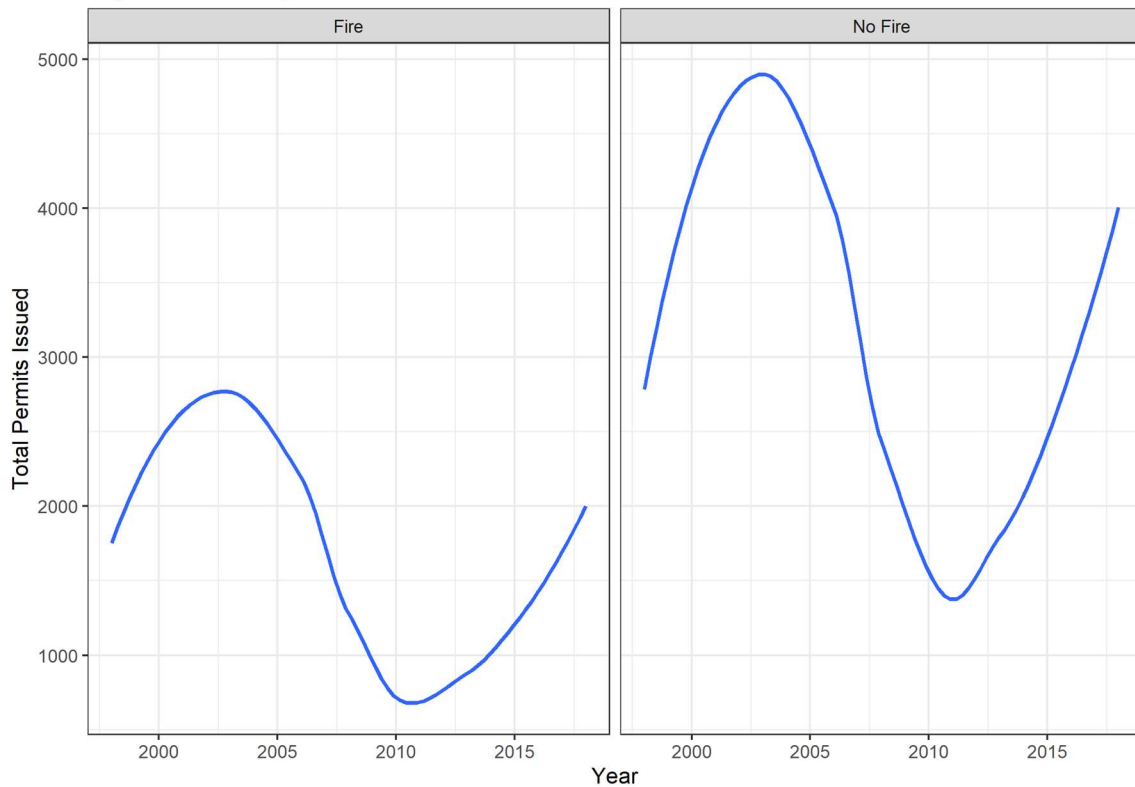
Where fire years are depicted, it is hypothesized that housing permits would see a sharp uptake in the following years compared to the general, state-wide trend due to the immediate housing needs of those displaced. However, no visual indicators exist in Figure 3, due in part to the fact that the general permitting patterns affecting all these counties are not yet held constant. The analysis in chapter 6 will provide clearer representations of these observations, but at its core the main regression model is a representation of what is occurring visually in these follow-up years after the red dots.

Another important factor to consider in Figure 3 is that many fires are observed in the later years of our observation period. Of the 26 counties and years observed with wildfire impacts, 10 of those instances occurred during the years 2017 and 2018. Therefore, generalized impacts to permitting practices in subsequent years following

wildfires will become increasingly variable for every additional year prior as the number of observations decreases.

4.4.4 Comparing the Treatment and Control Counties

Figure 4: Housing Permits Issued For Observed "Fire" vs. "No Fire" Counties Over Time



Source: U.S. Department of Housing and Urban Development

In order to generate meaningful results from the regression model, both observation groups and control groups need to be taken into account in order to determine variations from ordinary patterns. In this case, how and when housing permits are distributed need to be taken into account for all 58 counties within the population being observed, as well as factors used to determine effects, such as per capita income.

Figure 4 depicts a simple regression model for how a given county in both the “fire” and “non-fire” counties might issue housing permits from year-to-year. Compared to Figure 1, this model depicts a year-to-year observation, but regressed in order to

provide realistic comparisons unbiased by observation counts by group. The groups are subset by whether or not a given county experienced one of the 26 major wildfires incorporated in the model. Visually, there appears to be strong similarities between how each group distributed housing permits from year-to-year, with significant differences in the average number of total permits issued during this time as well as variation from year-to-year.

Counties affected by wildfires in this study tend to issue fewer housing permits than those which did not. This is not to say that this is the result of wildfire impacts--a more likely, prominent factor is that counties with major cities, which have dense populations and thus must generate more housing at a faster rate, are less likely to be in counties where wildfires are more common. WUI regions are often found in suburban or low-density housing regions, which would support this assumption. The primary regression model is set to analyze proportionate changes to housing permits issued, thus eliminating the concern for misleading results that are not representative for comparative purposes.

Chapter 5: Regression Analysis

5.1 Primary Regression Model Inputs

As described in the research methods section, the general structure of the regression model is that the total housing permits issued in a given year and county are a function of the number of structures destroyed from wildfires in each of the seven years prior to the observation year, as well as the per capita income of that region. The housing permit variable is logged in order to calculate the proportionate changes wildfire damages have on various regions, which may vary drastically in their average permit totals, as indicated previously with Figures 3 and 4. Interaction terms between the per capita income and fire destruction variables are utilized to explore endogenous correlations between independent variables, thus obscuring with independent-dependent variable relationships.

The dependent variable, `total_sf_mf_perm`, indicates the total number of residential building permits issued in a given county and year for multi-family and single-family development projects. As with the destruction counts correlated with each fire, these numbers reflect the approval for the development of entire structures, which may include multiple units. As discussed in Chapter 3, the issuance of a permit is not synonymous to the completed rebuilding of a destroyed home, but assumptions and analysis lead us to believe significant changes to the number of permits issued can translate to completed wildfire rehousing projects in the year following. By logging this term, the single-value increase in a given independent variable can be interpreted as a percent change to the expected permits issued based on the existing trend of permit

approvals in a given county and year. Therefore, the sign, magnitude, and t-value of each explanatory variable is necessary to properly interpret its relative impacts to permitting patterns.

The `struc_dest` variable, which indicates the number of structures destroyed by a wildfire specific to a year and county, is used to indicate both whether a fire is observed for a given entry and the scale of impact that fire had on the local housing stock. Therefore, the coefficient for these variables can be interpreted as the percent change each structure destroyed by a wildfire incurred upon the number of housing permits issued in the corresponding year, should a wildfire have occurred in that year. A “lag” function is utilized 7 times with incremental changes to the degree in order to indicate the 7 different post-fire years analyzed upon the same “`struc_dest`” variable. By logging the dependent variable, the coefficient for each year can be interpreted as a percent change to the number of housing permits issued for each structure destroyed, should a destructive wildfire have taken place in that respective year.

Heterogeneity is also explored in the pace of rebuilding across wealthy and lower-income counties. `over_40` is a binary variable with a value of 1 for counties where per capita income was above \$40,000 during the year of the wildfire observation. Across all counties in all years observed, the median per capita income is \$36,251 with a mean of \$39,462, so \$40,000 was chosen due to its relative closeness to these values and ease of interpretation. Although it is easy to prove that counties with higher per capita incomes generally issue more housing permits per year, this variable is included in the regression primarily to explore whether the coefficients on the `struc_dest` variable are biased towards or against wealthier counties, as well as whether such a relationship is significant

across all observations. In other words, the sign of the interaction term coefficients and their t-values indicate within the model whether the number of structures destroyed in a given year is more or less of a significant indicator between the “wealthy” and “poor” groups.

Variations of this setup were explored using different variables, including continuous (non-binary) per capita incomes, binary fire instances, poverty rates, regional populations, and grouped variables. However, `total_sf_mf_perm`, `struc_dest`, and `over_40` were chosen for the primary model due to their simplicity and functionality, such as their ability to be logged without error outputs. Output from these other regression models attempts can be viewed in the R Script `thesis_analysis`.

5.2 Primary Model Regression Results

Table 3: Primary Model With and Without Income Indicator

	<i>Dependent variable:</i>	
	log(total_mf_sf_perm)	
	(1)	(2)
lag(struc_dest, 7)	0.00006295*** (0.00002378)	0.00006087*** (0.00002341)
lag(struc_dest, 6)	0.00005953** (0.00002378)	0.00005781** (0.00002342)
lag(struc_dest, 5)	0.00005832** (0.00002379)	0.00005606** (0.00002342)
lag(struc_dest, 4)	0.00006114** (0.00002380)	0.00005720** (0.00002345)
lag(struc_dest, 3)	0.00004629* (0.00002392)	0.00003808 (0.00002342)
lag(struc_dest, 2)	0.00003314 (0.00002393)	0.00002726 (0.00002341)
lag(struc_dest, 1)	0.00002434 (0.00002551)	0.00003212 (0.00002336)
over_40	-0.10148930** (0.04861395)	
lag(struc_dest, 7):over_40	0.00001343 (0.00014603)	
lag(struc_dest, 6):over_40	0.00000815 (0.00014681)	
lag(struc_dest, 5):over_40	-0.00007496 (0.00014121)	
lag(struc_dest, 4):over_40	-0.00010189 (0.00013965)	
lag(struc_dest, 3):over_40	-0.00017992 (0.00012627)	
lag(struc_dest, 2):over_40	-0.00011199 (0.00012603)	
lag(struc_dest, 1):over_40	0.00006176 (0.00006476)	
Observations	1,206	1,206
R ²	0.02840454	0.01986006
Adjusted R ²	-0.05190703	-0.05358486
F Statistic	2.16923300*** (df = 15; 1113)	3.24489100*** (df = 7; 1121)
<i>Note:</i>		* p<0.1; ** p<0.05; *** p<0.01

5.2.1 Per Capita Income as a Correlated Factor

As indicated by Table 3, the output of the primary model includes several coefficients which are statistically significant. The primary model, depicted on the left, incorporates the isolated and interaction terms pertaining to fire-year per capita incomes. Although the significant relationship noted for the isolated term does not indicate any recovery differences between counties in the years following a wildfire instance, the lack of significance for any of the interaction terms indicates a failure to prove that income is a significant indicator of increased permits issued in any of these periods. For example, had the term $\text{lag}(\text{struc_dest}, 4) * \text{over_40}$ had a standard deviation significantly smaller than the one observed (0.00014), then high-income regions would be observed to have 1.02% less permits approved in the 4th year following the instance than low-income counties. Given these results, per capita income cannot be identified as a correlated factor to differences in the rebuilding timelines of different counties.

5.2.2 Years 1 Through 3 Post-Fire

Although the output of this model indicates that the occurrence of these wildfires may have a positive impact to permitting trends in the three years following their occurrence, these effects are smaller in comparison to later years and, mostly prominently, statistically insignificant at the 95% level. Interestingly, although large variations were associated with the coefficient for the interaction term pertaining to the year after a fire, $\text{lag}(\text{struc_dest}, 1) : \text{over_40}$, this is the only term where higher per capita incomes indicate a disproportionately larger effect on the increase in permits issued than observations in the low per capita income bracket. However, at a t-value of 0.87, too much variation across observations is present to prove this correlation.

5.2.3 Years 4 Through 7 Post-Fire

All of the coefficients for the impacts of structures destroyed 4-7 years prior to the observation year are positive, statistically significant, and (relatively) significant in magnitude. As indicated on Tables 3, coefficients range from .00583% to .0063% in percentage form as applied to the change in housing permits, accompanied with t-values in the 2.45 to 2.65 range. In other words, the model predicts that four years following a wildfire, each structure destroyed will result in a .00611% increase in housing permits issued with 99% confidence. These relative results are applied to more conceptual, comparative estimates with a scenario found in section 5.5. A second regression of the primary model without the income terms is depicted for comparison, with similarly significant effects observed in this time period.

When taking into account the outcomes of each fire year variable within the regression, it appears that with each year following a fire, the likelihood of housing permits being issued increases up until year 7. At this point, within the constraints of this model, statistical significance, and thus certainty that increases in housing permits will be present, peaks. However, the quick average-scenario calculations indicate very small observed changes to increased permitting activity in comparison to the destruction of the fire itself.

5.3 Alternative Approaches and Errors

In order to ensure that the model setup is reflective of the reality it is attempting to explain, several variations of the regression were tested. Statistical significance, heterogeneity, and other insights are employed to shine light onto flaws outside the fixed-

effect assumptions of the model type. Therefore, regressions specific to non-fire recovery years, housing permit types, and income indicators are substituted in for comparison.

5.3.1 “Lead” Years

Table 4: Fire Impacts on Housing During and Before Its Occurance

	<i>Dependent variable:</i>
	log(total_mf_sf_perm)
lead(struc_dest, 7)	-0.00000923 (0.00002381)
lead(struc_dest, 6)	0.00000709 (0.00002382)
lead(struc_dest, 5)	0.00000405 (0.00002384)
lead(struc_dest, 4)	0.00001965 (0.00002384)
lead(struc_dest, 3)	0.00001132 (0.00002384)
lead(struc_dest, 2)	-0.00000638 (0.00002384)
lead(struc_dest, 1)	-0.00000372 (0.00002385)
struc_dest	-0.00000981 (0.00002385)
Observations	1,206
R ²	0.00134826
Adjusted R ²	-0.07444227
F Statistic	0.18901180 (df = 8; 1120)
Note:	* p<0.1; ** p<0.05; *** p<0.01

One concern of the model is that if significant impacts to housing permit practices are found in the years after a wildfire, no significant impacts should be indicated in the years of or prior to these fires. Known widely as the parallel trend assumption, a difference-in-difference model such as this where a singular event differentiates “before” and “after” periods, significant results between the control and observation groups should

be constant over time. In other words, the coefficients for “pre-fire” years, or the impacts of structures destroyed in the future on current permitting practices, should not be significant. This pre-trends analysis can be used as supportive evidence to argue that counties with and without fires experienced similar trends in housing permitting prior to the fire, and only diverged after the fires.

In order to test this result, permits issued were regressed on the “lead” fire years in the same format done for the primary model, but rather than analyzing “fire years” 1-7, “pre-fire years” 1-7, as well as the year of, were used in the model. The presence of the per capita income variable and subsequent interaction terms were removed from this analysis, although results when running the original model with lead years added on presented similar results

As indicated by Table 4, none of the effects of structures destroyed in future time periods presented significant results. With t-values in the absolute value range of 0.1559 - 0.8241, there is no signs of any relationship where the presence of future or current fires affect current permitting practices. This indicates that the significant results found in the original model display an unusual, diverging trend when compared to the normal permitting patterns, thus the fire “disturbance” of the model is overwhelmingly the primary driver of these resulting impacts.

5.3.2 Single-Family vs. Multi-Family Permitting Comparison

Table 5: Primary Model Assessment with Single-Family and Multi-Family Permit Comparison

	<i>Dependent variable:</i>	
	log(total_sf_perm) (1)	log(total_mf_perm) (2)
lag(struc_dest, 7)	0.00005997*** (0.00002216)	-0.00006336 (0.00005369)
lag(struc_dest, 6)	0.00005406** (0.00002217)	0.00011968 (0.00008171)
lag(struc_dest, 5)	0.00005205** (0.00002217)	0.00009044 (0.00008157)
lag(struc_dest, 4)	0.00005572** (0.00002218)	0.00005446 (0.00008182)
lag(struc_dest, 3)	0.00003973* (0.00002230)	0.00007422 (0.00008190)
lag(struc_dest, 2)	0.00002338 (0.00002230)	0.00007312 (0.00008226)
lag(struc_dest, 1)	0.00001142 (0.00002377)	0.00016425* (0.00008960)
over_40	-0.07783605* (0.04530962)	-0.27287620** (0.12193200)
lag(struc_dest, 7):over_40	-0.00000435 (0.00013610)	0.00013680 (0.00031621)
lag(struc_dest, 6):over_40	-0.00003379 (0.00013683)	-0.00001035 (0.00032384)
lag(struc_dest, 5):over_40	-0.00011092 (0.00013161)	-0.00009313 (0.00030590)
lag(struc_dest, 4):over_40	-0.00009911 (0.00013016)	-0.00016445 (0.00030237)
lag(struc_dest, 3):over_40	-0.00010695 (0.00011769)	-0.00038043 (0.00032367)
lag(struc_dest, 2):over_40	-0.00002773 (0.00011746)	-0.00020336 (0.00032240)
lag(struc_dest, 1):over_40	0.00014203** (0.00006036)	-0.00035777** (0.00015810)
Observations	1,206	900
R ²	0.02936579	0.01813284
Adjusted R ²	-0.05086633	-0.09109836
F Statistic	2.24486400*** (df = 15; 1113) 0.99602550 (df = 15; 809)	

Note:

* p<0.1; ** p<0.05; *** p<0.01

A critical assumption of the model is that, in lack of housing unit-based destruction and recovery values, total structure data would reflect a similar proportionate trend as to how communities are rebuilding. Although the main model maps out when rehousing is apparent, the question of *how* rehousing occurs, such as the density and structure type, is not clear.

In order to assess this question, and to uncover information regarding the number of units versus structures being rebuilt, the model was adjusted to focus on just the single family and multi-family development projects approved during these time periods. Many fires impacted primarily suburban regions composed of single-family structures, such as the Tubbs Fire, which tore through the suburban regions of Santa Rosa (Herrera, 2019). Therefore, if a significant number of multi-family structures is found, this could indicate that rebuilding efforts are focused towards making regions denser as opposed to simply replacing single-family homes with more single family homes.

As indicated by Table 5, significant impacts to single-family permits were observed, but not when subsetting for multi-family permits. Within each model, observation years where no permits of these respective types were identified in a given county were omitted in order to log the variables without error terms. This meant omitting 5 observations for the single family regression and 311 for the multi-family county, which may be contributing to the insignificant values of the multi-family regression in Table 5. However, these outcomes appear to indicate that most structures are being replaced with the same, single-family homes associated with the regions commonly impacted by wildfires.

5.3.3 12 Year Approach

Table 6: Primary Model Comparison to 12-Year Equivalent

	<i>Dependent variable:</i>	
	log(total_mf_sf_perm)	
	(1)	(2)
lag(struc_dest, 12)		0.00001962 (0.00002395)
lag(struc_dest, 11)		0.00004337* (0.00002393)
lag(struc_dest, 10)		0.00005392** (0.00002395)
lag(struc_dest, 9)		0.00007087*** (0.00002395)
lag(struc_dest, 8)		0.00008007*** (0.00002394)
lag(struc_dest, 7)	0.00006295*** (0.00002378)	0.00008198*** (0.00002393)
lag(struc_dest, 6)	0.00005953** (0.00002378)	0.00007810*** (0.00002393)
lag(struc_dest, 5)	0.00005832** (0.00002379)	0.00007679*** (0.00002393)
lag(struc_dest, 4)	0.00006114** (0.00002380)	0.00007949*** (0.00002394)
lag(struc_dest, 3)	0.00004629* (0.00002392)	0.00006488*** (0.00002407)
lag(struc_dest, 2)	0.00003314 (0.00002393)	0.00005119** (0.00002403)
lag(struc_dest, 1)	0.00002434 (0.00002551)	0.00004198 (0.00002558)
over_40	-0.10148930** (0.04861395)	-0.08954075* (0.04840391)
lag(struc_dest, 12):over_40		-0.00008501 (0.00014449)
lag(struc_dest, 11):over_40		0.00004161 (0.00015559)

lag(struc_dest, 10):over_40		0.00017264 (0.00015454)
lag(struc_dest, 9):over_40		0.00015660 (0.00015125)
lag(struc_dest, 8):over_40		0.00022426 (0.00016617)
lag(struc_dest, 7):over_40	0.00001343 (0.00014603)	0.00000371 (0.00015958)
lag(struc_dest, 6):over_40	0.00000815 (0.00014681)	-0.00007761 (0.00016002)
lag(struc_dest, 5):over_40	-0.00007496 (0.00014121)	-0.00013425 (0.00015178)
lag(struc_dest, 4):over_40	-0.00010189 (0.00013965)	-0.00018244 (0.00015360)
lag(struc_dest, 3):over_40	-0.00017992 (0.00012627)	-0.00014745 (0.00012991)
lag(struc_dest, 2):over_40	-0.00011199 (0.00012603)	-0.00005970 (0.00012959)
lag(struc_dest, 1):over_40	0.00006176 (0.00006476)	0.00006057 (0.00006475)
Observations	1,206	1,201
R ²	0.02840454	0.05345343
Adjusted R ²	-0.05190703	-0.03447713
F Statistic	2.16923300 *** (df = 15; 1113)	2.48025200 *** (df = 25; 1098)
<i>Note:</i>		* p<0.1; ** p<0.05; *** p<0.01

A missing component of the main regression model is when regions appear to stop issuing more housing permits at significant, noticeable rates. Therefore, the model could be expanded to add more years up until the point where the coefficient for a struc_dest in a later lag year is no longer significant at the 95% level.

As depicted in Table 6, the original model is expanded to analyze impacts up until 12 years following the instance of a wildfire. Not only do we see that as late as 10 years later are there significant positive impacts to housing permits issued at the 95% confidence level, but significant impacts are now noticed just two years following the

fire. For each structure destroyed by a wildfire, there is an expected 0.00795% increase in housing permits issued four years following the event, an increase of .00185 percentage points from the original model. Compared to the original model, the magnitude of impacts from each structure destroyed also increased, to be elaborated on and compared in section 5.5. All interaction terms continue to exhibit no significance, while the significance of being in-or-out of the \$40,000 per capita income bracket falls from the 95% confidence level to 90%.

Although this model provides more compelling results, it is only regarded as a noteworthy application due to the limitation of observation points this far out into the future based on the fire years observed. The average year in which fires were observed for this analysis is 2012.92, leaving just five years of permit data to be incorporated into the model for a large number of fires. Due to this, along with the clustering of fires in later years, interpretations of this 12-year model are hesitant due to the lack of input data. Only four observations accommodate the entire 12-year period, while 8 unique counties and time periods are able to be incorporated at the 8-year benchmark.

5.4 Averaged Scenario for the Application of Coefficients

Table 6: "Average Fire County" Scenario

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
year	21	2,008.000	6.205	1,998	2,003	2,013	2,018
total_mf_sf_perm	21	3,211.766	1,341.948	950.462	2,305.846	3,961.462	5,682.154
total_sf_perm	21	1,782.084	1,065.342	554.077	798.385	2,662.923	3,635.923
total_mf_perm	21	1,429.681	512.263	394.692	1,063.846	1,775.846	2,113.385
total_sf_mf_exist	21	450,713.600	19,309.980	417,602.800	434,163.800	465,644.600	476,617.200
per_cap_inc	21	38,478.040	8,099.697	25,722.540	32,102.460	43,100.920	54,044.000

In order to put the validated coefficients of the models into perspective, a general scenario is utilized to estimate predicted outcomes in averaged totals as opposed to proportionate changes. This “average fire county”, which is summarized in Figure 7, is the result of averaging the permits issued and per capita income of all 13 counties impacted by wildfires in each year. By making use of a situation where a fire of median destruction from the observation pool, 534 structures, and the mean yearly values for permit approvals and per capita incomes across all 13 counties observed in the observation group, comparisons can be made regarding the predicted outcomes of these models.

In the original model, a wildfire and “average” county in this setup where the fire occurred in 2008 would have incurred positive, significant impacts to housing in the years 2012-2015. When applying the fire impacts to these coefficients, we find that housing permits are increased by 3.26%, 3.11%, 3.18%, and 3.36%, respectively. When applied to the averaged permits issued in these time periods, this translates to 53.6, 71.8, 76.8, and 106.4 permits approved due to this isolated impact, or a total of 309 housing permits approved over this time period. In other words, the model predicts that 58% of all houses destroyed by a wildfire in 2008 will have been approved for reconstruction 7 years later. Assuming there is at least a one year interim period between the approval of a housing permit and its finalized construction, this model implies that it would actually take 8 years following a wildfire in this scenario for 58% of houses to be rebuilt.

In the 12 year model, the same process can be applied to see how the significant impacts of an expected wildfire compare to our previous estimates. Assuming the fire occurred in 2008, significant impacts to housing permits issued would be observed

between 2010-2018. These impacts would begin with an 2.73% increase in 2010, peaking with an 4.38% increase in 2015 and finishing with a 2.88% increase in 2018. In these same years under the averaged scenario, this translates to an increase of 31.3 permits in 2010, 138.5 in 2015, and 98.6 in 2018. In total, 485 housing permits are predicted to be issued between 2010-2015 (the 7th year following the wildfire), and 849 by the end of 2018. This translates to about 91% total recovery during the same 8-year period as the original model, and an actual acceleration of housing caused by the fire in generating 59% more housing on top of recovering all structures destroyed in 2008 by the end of 2019.

These results further support the skepticism that the 12 year model is biased due to the unlikeliness that a fire would generate more housing permits beyond the recovery of the structures destroyed. Therefore, this large bias may be apparent to some extent in the primary 7-year model, so interpretation of estimates pertaining to the resulting recovery rates are cautioned.

Chapter 6: Conclusion

6.1 Testing Hypothesis 1-4

Of the four hypotheses presented in Chapter 1, only the fourth was entirely correct. H_A^1 , which assumed there would be significant and positive impacts to permits issued in the 5 years following a fire instance in the model, was disproved by the lack of significance for the first, second, and third years following the fire instance year. This could be explained by a variety of uncertain factors, including delayed responses in mobilizing rehousing efforts, large regional variations in policies to incentivize redevelopment applications, and the decisions made by displaced individuals to rebuild or relocate. This is not to say that there was no significant change to the housing permits issued during these time periods for any of these counties in the observed periods. However, these results indicate that a more accurate model of recovery was reflected in the papers by Alexandre et al. (2014) and Mockrin et al. (2015), where it was denoted that moderate proportions of rebuilding were noticed beginning around four years following the wildfire occurrences.

As for the second hypothesis, no significant differences in permitting practices were observed between counties in different per capita income brackets at the time of wildfire occurrence in any of the follow up years, let alone the first two. This indicates that disparities in the wealth of a community impacted by a wildfire may not be a critical factor when considering the time or likelihood of a community to rebuild their housing at similar rates. This may be explained by the role of federal aid agencies such as FEMA and USDA, which often become the primary funders in locally-facilitated recovery programs as discussed in Chapter 3. The programs offered by these agencies not only

ignore the socioeconomic characteristics of regions when deciding to provide aid, but often provide funds and transitional housing specifically for low-income homeowners.

In the primary model, the 7th year following a wildfire was found to be the year during which housing permits were most significantly approved at higher rates due to the wildfire occurrence, thereby disproving the null hypothesis of the third hypothesis. However, with just a .00046 percentage point difference in increased permits issued per structure destroyed, the differences in this effect are very slim between the two years. Since neither per capita income brackets nor wildfire impacts were found to have a significant effect on housing permits issued 3 years following a wildfire, the second condition of that hypothesis is disproved as well.

The fourth hypothesis, that significant impacts would be observed for single family permit approvals but not multifamily residential projects, was proven correct. This provides further evidence that homeowners are likely rebuilding their single family homes with other single family homes, maintaining the original density of the impacted regions. If significant portions of multifamily residences were destroyed by these fires, or significant numbers of formerly single family residences were replaced with multifamily units, we would expect significant results from the multifamily regression. However, assuming multifamily structures are generally not replaced by single family homes, the trend clearly appears to be a maintained single family redevelopment.

6.2 Research Limitations

A number of limitations and potential oversights may be contributing to a bias in the finalized results. Although the nature of the regression model holds most time-or-

regional characteristics constant across all observations, other year-and-county specific occurrences not considered within the model could be introducing biases in our results if they contain a causal relationship with housing permit issuance patterns. Furthermore, the use of natural control and observation groups may not be entirely randomized, as certain counties are more susceptible to large-scale damages and/or more frequent occurrences of wildfires. As discussed with the 12-year model, the clustering of observed fires in later time periods could be affecting the significance and magnitude of impacts of wildfires in the years immediately following versus the more significant effects observed in later years. Lastly, the use of two proxies--housing permits issued and counties--present require estimates regarding the timing and relative impacts imposed on communities when replaced by more ideal datasets, such as houses specifically rebuilt from wildfires and city-based regional groupings.

6.3 Academic and Policy Recommendations

Based on the methods and interpretations of results from the research and literature review of this paper, the researcher recommends that further time-series analysis be conducted across a large number of fire observations to better understand the expected outcomes of these disasters. Similar approaches could be applied by categorizing interventions, incorporating further county-level characteristics, and generally expanding upon the applications and extent of the wildfire destruction database compiled for this research. Although case-studies and interviews have provided insights on general trends or single-occurrence metrics, a model in which homeowner perceptions, government interventions, rehousing requirements, and regional characteristics could be

explored to further recommend the best actions to be taken in minimizing future wildfire risks and displacement periods.

Until such a time where these complex models exist, the findings of this research model are intended to make aware the presumed financial, political, and housing development process obstacles barring many homeowners from initiating rebuilding efforts soon after the destruction from a wildfire. Even with the known motives of many recovery programs to speed up the rehousing process of communities, as identified in at least two highly-impacted communities in case-studies, there appears to be struggles beyond financing a building project in this process (Herrera, 2019). With future risks and regulatory checks on rehousing practices taken into consideration, the researcher urges policy makers to further explore both short and long-term solutions to the matter at hand. State and local precautionary policies, such as the transitional housing and emergency grants provided by federal agencies such as FEMA, could serve to support the immediate housing needs of displaced residents, while rezoning and precautionary zoning on encroached WUI regions could prevent the severity and frequency at which homeowners are put into this dilemma in the first place. While the results of this study indicate that existing policies aimed towards rapid rehousing may be falling short of expectations, policy makers are also urged to recognize the long-term implications of rebuilding over high-risk regions, and to acknowledge to potential benefits of a relocation assistance program based on existing fire-risk assessment models.

Work Cited

- Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, 113(42), 11770–11775. DOI: 10.1073/pnas.1607171113
- Abrams, J.B., Knapp, M., Paveglio, T.B., Ellison, A. & Moseley, C. (2015). Re-envisioning community wildfire relations in the U.S. West as adaptive governance. *Ecology & Society*, 20(3), 34. DOI: <http://dx.doi.org/10.5751/ES-07848-200334>
- Adolphe, J. (2018, September 18). Why are California wildfires so bad? *The Guardian*. Retrieved from <https://www.theguardian.com/world/ng-interactive/2018/sep/20/why-are-california-wildfires-so-bad-interactive>
- Alexandre, P.M., Mockrin, M.H., Stewart, S.I., Hammer, R.B., & Radeloff, V.C. (2014). Rebuilding and new housing development after wildfire. *International Journal of Wildland Fire*, 24(1), 138-149. DOI: <https://doi.org/10.1071/WF13197>
- Bardhan, A. & Walker, R. A. (2010). California, pivot of the Great Recession. *UC Berkeley: Institute for Research on Labor Employment*. Retrieved from <https://escholarship.org/uc/item/0qn3z3td>
- Barron, L. & Gajanan, M. (2017, October 17). California's Wildfires Have Become Bigger, Deadlier, and More Costly. Here's Why. *Time Magazine*. Retrieved from <https://time.com/4985252/california-wildfires-fires-climate-change/>
- Bliss, L. (2019, October 29). California Contemplates a Dark and Fiery Future. *CityLab*. Retrieved from <https://www.citylab.com/environment/2019/10/california-kincade-fire-blackouts-sonoma-wind-climate-change/600931/>
- Bryant, B. P., & Westerling, A. L. (2014). Scenarios for future wildfire risk in California: links between changing demography, land use, climate, and wildfire. *Environmetrics*, 25(6), 454–471. DOI: 10.1002/env.2280
- California Department of Fish and Wildlife. (n.d.). A Summary of the California Environmental Quality Act (CEQA). Retrieved from: <https://wildlife.ca.gov/Conservation/CEQA/Purpose>

- CAL FIRE. (2019). Top 20 Most Destructive California Wildfires. California Department of Forestry and Fire Protection. Retrieved from https://www.fire.ca.gov/media/5511/top20_destruction.pdf
- California Energy Commission. (2018). *Wildfire simulations for California's fourth climate change assessment: projecting changes in extreme wildfire events with a warming climate*. (CEC Publication No. CCCA4-CEC-2018-014).
- California Natural Resource Agency. (2018). *Wildfire simulations for California's fourth climate change assessment: the impact of changing wildfire risk on California's residential insurance market*. (CNRC Publication No. CCCA4-CNRA-2018-008)
- Cal OES. (n.d.). Housing Assistance. California Wildfires Statewide Recovery Resources. Retrieved from <https://wildfirerecovery.caloes.ca.gov/general-info/housing-assistance/?cat=81>
- CBS. (2019, October 28). Doctor Warns Of Lung Damage Linked To Wildfire Smoke As Getty Fire Burns Near Sepulveda Pass. Retrieved from <https://losangeles.cbslocal.com/2019/10/28/lung-damage-wildfire-smoke/>
- City of San Luis Obispo. (n.d.). A Customer Guide to the Building Permit Process. Retrieved from <http://www.slocity.org/home/showdocument?id=3878>
- Clark, J. (1988). Effect of climate change on fire regimes in northwestern Minnesota. *Nature*, 334; 233–235. DOI:10.1038/334233a0
- CWAM. (n.d.). California Watershed Assessment Manual, Volume II – Fire and Fuels. Retrieved from <http://cwam.ucdavis.edu/>
- Davies, I. P., Haugo, R.D., Robertson, J.C. & Levin, P.S. (2018). The unequal vulnerability of communities of color to wildfire. *PLoS ONE*, 13(11). DOI: <https://doi.org/10.1371/journal.pone.0205825>
- Dixon, L., Tsang, F. & Fitts, G. (2018). *The impact of changing wildfire risk on California's residential insurance market*. (Report No. CCCA4-CNRA- 2018-008). California: California's Fourth Climate Change Assessment.
- FEMA. (2019). Building Science. Federal Emergency Management Agency. Retrieved from <https://www.fema.gov/building-science>

- Gibbens, S. (2018, August 28). Survey Reports on Average Construction Time for New Homes. Green Building News. Retrieved from <https://www.greenbuildingadvisor.com/article/survey-reports-average-construction-time-new-homes>
- Gibbens, S. (2019, October 31). Wildfires pose new threats as homes burn, releasing toxic fumes. *National Geographic*. Retrieved from <https://www.nationalgeographic.com/science/2019/10/airborne-health-concerns-emerge-from-california-wildfire/>
- Helvarg, D. (2019, December 20). How will California prevent more mega-wildfire disasters? *National Geographic*. Retrieved from <https://www.nationalgeographic.com/science/2019/12/how-will-california-prevent-more-mega-wildfire-disasters/#close>
- HCD. (n.d.). Processing and Permitting Procedures. California Department of Housing and Community Development. Retrieved from <https://www.hcd.ca.gov/community-development/building-blocks/constraints/processing-permitting-procedures.shtml#sample>
- Herrera, Dana. (2019). Assessing local government actions in response to wildfires. *California State Polytechnic University, Pomona Department of Urban and Regional Planning*. Retrieved from: <http://broncoscholar.library.cpp.edu/handle/10211.3/213261>
- Kelly, H. (2018). Understanding Wildfire in California: What the CSU is Learning. The California State University, retrieved from <https://www2.calstate.edu/csu-system/news/Pages/understanding-fire.aspx>
- Kramer, H. A., Mockrin, M.H., Alexandre, P.M., Stewart, S.I. & Radeloff, V.C. (2018). Where wildfires destroy buildings in the US relative to the wildland–urban interface and national fire outreach programs. *International Journal of Wildland Fire*, 27(5), 329-341.
- Lazo, A. & Carlton, J. (2019, October 10). Power Outage in California Affects Millions as PG&E Tries to Avoid Wildfire: Seeking to limit fire risk amid high winds, utility cuts electricity across Northern California. *The Wall Street Journal*. Retrieved from <https://www.wsj.com/articles/millions-in-california-begin-losing-power-as-pg-e-tries-to-avoid-wildfire-11570632347>

- Keeley, J.E. (1991). Seed germination and life history syndromes in the California chaparral. *The Botanical Review*, 57(2), 81. DOI: <https://doi.org/10.1007/BF02858766>
- Mann, M. L., Berck, P., Moritz, M. A., Batllori, E., Baldwin, J. G., Gately, C. K., & Cameron, D. R. (2014). Modeling residential development in California from 2000 to 2050: Integrating wildfire risk, wildland and agricultural encroachment. *Land Use Policy*, 41, 438–452. DOI: 10.1016/j.landusepol.2014.06.020
- Martin, R.E. & Sapsis, D.B. (1995). A synopsis of large or disastrous wildland fires. *Pacific Southwest Research Station, Forest Service, U.S. Department of Agriculture*, 35-38. DOI: <https://www.fs.usda.gov/treearch/pubs/27406>
- Mockrin, H.M., Fishler, H.K. & Stewart, S.I. (2018). Does wildfire open a policy window? Local government and community adaptation after fire in the United States. *Environmental Management*, 62(2), 210-228. DOI: <https://doi.org/10.1007/s00267-018-1030-9>
- Mockrin, M.H., Stewart, S.I., Radeloff, V.C. & Hammer, R.B. (2016). *International Journal of Wildland Fire*, 25(11), 1144-1155. DOI: <https://doi.org/10.1071/WF16020>
- Mockrin, M.H., Stewart, S.I., Radeloff, V.C., Hammer, R.B. & Alexandre, P.M. (2015). Adapting to wildfire: rebuilding after home loss. *Society & Natural Resources*, 28(8), 839-856. DOI: <https://doi.org/10.1080/08941920.2015.1014596>
- Prunicki, M., Kelsey, R., Lee, J., Zhou, W., Smith, E., Haddad, F., et al. (2019). The impact of prescribed fire versus wildfire on the immune and cardiovascular systems of children. *Allergy: European Journal of Allergy and Clinical Immunology*, 74(10), 1989-1991.
- Quigley, J. M. & Raphael, S. (2005). Regulation and the high cost of housing in California. *American Economic Review*, 95(2), 323-328. DOI: 10.1257/000282805774670293
- Ryan, R. L. & Hamin, E. (2008). Wildfires, communities, and agencies: stakeholders' perceptions of postfire forest restoration and rehabilitation. *Journal of Forestry*, 106(7), 370–379. DOI: <https://doi.org/10.1093/jof/106.7.370>

- Schumann III, R.L., Mockrin, M.H., Syphard, A., Whittaker, J., Price, O., Gaither, C.J., Emrich, C.T. & Butsic, V. (2019). Wildfire recovery as a “hot moment” for creating fire-adapted communities. *International Journal of Disaster Risk Reduction*. DOI: <https://doi.org/10.1016/j.ijdr.2019.101354>
- Singleton, M. P., Thode, A.E., Sanchez Meador, A.J. & Iiguez, J.M. (2018). Increasing trends in high-severity fire in the southwestern USA from 1984 to 2015. *Forest Ecology and Management*, 433, 709-719. DOI: <https://doi.org/10.1016/j.foreco.2018.11.039>
- Smith-Heimer, J. & Hitchcock, J. (2019). CEQA and housing production: 2018 survey of California cities and counties. *Journal of Environmental Practice*, 21(2), 69-84. DOI: <https://doi.org/10.1080/14660466.2019.1609848>
- Syphard, A. D., Keeley, J. E., Massada, A. B., Brennan, T. J., & Radeloff, V. C. (2012). Housing Arrangement and Location Determine the Likelihood of Housing Loss Due to Wildfire. *PLoS ONE*, 7(3). DOI: 10.1371/journal.pone.0033954
- Tikkanen, L. (2017). San Quentin State Prison. Encyclopædia Britannica. Retrieved from <https://www.britannica.com/topic/San-Quentin-State-Prison>
- US Forest Services. (2005). *Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model* (USDA Report No. RMRS-GTR-153). Washington DC: US Department of Agriculture
- U.S Forest Services. (2001). *Urban Wildland Interface Communities Within the Vicinity of Federal Lands That Are at High Risk From Wildfire* (Doc. Citation 66 FR 751). Washington DC: National Archives and Records Administration.
- Westerling, A.L. & Bryant, B.P. (2007). Climatic change and wildfire in California. *Climate Change*, 87(Suppl 1), 231. DOI: <https://doi.org/10.1007/s10584-007-9363-z>