ESSAYS ON THE ECONOMIC VALUATION OF WILDFIRES

by

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ABSTRACT

This thesis studies changes and differences in safety preferences as revealed by the housing market through the capitalisation of wildfire risk into property prices. To explain changes or differences in property prices, we implement the hedonic price method using high-quality geographic information system data on utility-bearing attributes specific to the property and its location. For this purpose, we focus on Western Australia during 2010-2019, a region of high wildfire risk with recent policy changes. CHAPTER 1 studies the near-miss effect of wildfires, i.e., the impact of a wildfire disaster on the area free from damage but subject to information effects. These information effects may alter households' risk perception depending on their experience during the event. The wildfire disaster that we analyse is the Waroona Fire of 2016. To identify the near-miss effect, we rely on the use of difference-in-differences and a multidimensional near-miss area defined by proximity to the burn scar and receiving warnings during the fire event. Our findings suggest that the proximity treatment effect is positive due to a risk reduction effect from burnt fuel that dominates over any disamenity impacts. On the other hand, the warning treatment effect is negative, suggesting an increase in risk perception due to vulnerability feelings. CHAPTER 2 studies the introduction of wildfire risk maps in 2015, known in Western Australia as 'bushfire prone area' maps. These maps were received with surprise by residents and areas mapped as 'risky' faced more stringent planning and building regulations. Taking advantage of the sharp boundaries that divide designated from non-designated areas, we use a regression discontinuity design to investigate the price differential for designated properties. We find that properties within bushfire prone areas are sold at a lower price, and results suggest that this discount is moreover driven by a pure information shock that increases risk perceptions, rather than by any

predetermined risk perceptions or the more stringent planning and building regulations that apply to new builds. CHAPTER 3 studies preferences for prescribed fires by accounting for its exposure in terms of number of fires and area burnt. Prescribed fires are used by land managers to reduce the likelihood of uncontrollable wildfires, but generate disamenity impacts, such as smoke haze and road closures. These fires also face strong opposition from conservationists. Using property fixed effects and controlling for wildfire exposure, we find a positive preference for prescribed fires, and stronger results for more recent fires, which we attribute to the depreciating nature of risk reducing interventions over time and/or to availability heuristics due to recent fires being easier to retrieve. Our results are also stronger when we use the number of fires, than when we use area burnt, suggesting households pay more attention to the frequency component of risk, rather than consequence. Additionally, properties with no wildfire exposure are sold at a price significantly higher, suggesting perhaps that households' demand for prescribed fires is higher in the absence of the risk reduction effect of wildfires. Our findings also suggest that the use of property fixed effects is important for an appropriate incorporation of time-constant attributes.

Overall, our findings suggest that risk perception updates are capitalised into the housing market, particularly in areas that are wildfire prone, as that of Western Australia; meaning that policy makers do have the potential to alter people's beliefs about risk. Amid an increasing risk of wildfires across the globe, much more research is needed on identifying misperceptions on risk, tools for correction, and households' preferences for forest management practices.

DEDICATION

To my parents, Gustavo and Marcela, who are always on my thoughts, and who pray for me every day from our home in Lima, Peru.

A mis padres, Gustavo y Marcela, a quienes llevo siempre en mis pensamientos y quienes me tienen siempre en sus rezos desde nuestro hogar en Lima, Perú.

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This thesis uses publicly available and open data published by the Australian Government and the Government of Western Australia licensed under Creative Commons Attribution 4.0 International (CC BY 4.0) and under Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0). Property data are provided under licence by Australian Property Monitors.

I am grateful for the encouragement, advice, and insightful comments from my supervisors, David J. Maddison and Allan Beltrán Hernández. David and Allan have also contributed in editing and conceptualizing CHAPTER 1 and CHAPTER 2 of this thesis.

I am also grateful to Mike Meinema, Fire Policy & Planning Manager at the Department of Biodiversity, Conservation and Attractions in Western Australia, who kindly answered a pile of emails and agreed to a videochat to help me understand the process of prescribed burning in Western Australia and the fire history dataset.

TABLE OF CONTENTS

ABSTRACT 1
DEDICATION 3
ACKNOWLEDGEMENTS 4
LIST OF UNITS OF MEASUREMENT ABBREVIATIONS 12
INTRODUCTION 13
CHAPTER 1 THE NEAR-MISS EFFECT OF WILDFIRE DISASTERS 21
ABSTRACT 22
1.1 INTRODUCTION 23
1.2 LITERATURE REVIEW 27
1.3 METHODOLOGY 41
1.3.1 The hedonic price method 41
1.3.2 Difference-in-differences as identification strategy 48
1.3.3 Empirical estimation of the near-miss effect 50
1.4 THE WAROONA FIRE OF 2016 51
1.5 DATA 53
1.6 RESULTS 58
1.7 DISCUSSION 60
1.8 CONCLUSION 67
1.9 APPENDIX 69
Appendix A: Main Results 69
Appendix B: Additional Results 77
Appendix C: Data 83
CHAPTER 2 WILDFIRE RISK AND PROPERTY PRICES: A DISCONTINUITY ANALYSIS OF THE INTRODUCTION OF BUSHFIRE PRONE AREA MAPS 86
ABSTRACT 87
2.1 INTRODUCTION 88
2.2 LITERATURE REVIEW 91
2.3 METHODOLOGY 99
2.4 DATA 101
2.5 RESULTS 108
2.6 DISCUSSION 111
2.7 VALIDATION TESTS 115
2.8 CONCLUSIONS 120

2.9 APPENDIX 122
CHAPTER 3 FOREST MANAGEMENT PRACTICES AND SAFETY PREFERENCES: DO HOUSEHOLDS WELCOME PRESCRIBED BURNING? 123
ABSTRACT 124
3.1 INTRODUCTION 125
3.2 LITERATURE REVIEW 130
3.3 PRESCRIBED BURNING IN WESTERN AUSTRALIA 141
3.4 METHODOLOGY 145
3.5 DATA 152
3.6 RESULTS 158
3.7 DISCUSSION 169
3.8 CONCLUSIONS 177
3.9 APPENDIX 180
CONCLUSIONS 185
REFERENCES 193

LIST OF TABLES

CHAPTER 1 THE NEAR-MISS EFFECT OF WILDFIRE DISASTERS

Table 1.2.1: Literature review search 28

Table 1.2.2: HPM applications for Australia........ 39

Table 1.5.1: Examples of emergency warning alerts........ 56

Table 1.5.2: Number of observations for treatment and control groups........ 58

Table 1.6.1: Main Results 59

Table 1.7.1: Placebo test........ 63

Table 1.7.2: Additional Results 64

Table 1.7.3: Average treatment effects for Model 2A........ 67

Table 1.10.1: Estimations Results for Model 1 69

Table 1.10.2: Estimation Results for Model 2A 71

Table 1.10.3: Estimations Results for Model 2B........ 74

Table 1.10.4: Estimations Results for Model 2C........ 77

Table 1.10.5: Estimation Results for Model 2D 80

Table 1.10.6: Primary data sources 83

Table 1.10.7: Summary statistics........ 84

Table 1.10.8: Property type frequency 85

CHAPTER 2WILDFIRE RISK AND PROPERTY PRICES: A DISCONTINUITY ANALYSIS OF THE INTRODUCTION OF BUSHFIRE PRONE AREA MAPS

Table 2.4.1: Summary statistics for treatment and control groups and pre and post introduction of BPA maps........ 106

Table 2.5.1: RD Point Estimates 110

Table 2.6.1: RD point estimates for pre-treatment and treatment periods 113

Table 2.6.2: RD point estimates for the 'regulation effect'........ 114

Table 2.7.1: Validation test - Manipulation test using local polynomial density estimation........ 117

Table 2.7.2: Validation test, donut-hole approach 118

Table 2.7.3: Validation test - Sensitivity to bandwidth choice 119

Table 2.9.1: BPA designations...122

CHAPTER 3 FOREST MANAGEMENT PRACTICES AND SAFETY PREFERENCES: DO HOUSEHOLDS WELCOME PRESCRIBED BURNING?

Table 3.2.1 Literature review search description...130

Table 3.4.1: Equations.. 151

Table 3.4.2: Definition of variables.. 151

Table 3.5.1: Exposure to fire...155

Table 3.5.2: Summary statistics for all observations...156

Table 3.5.3: Summary statistics for treated observations 157

Table 3.6.1: Main results 159

Table 3.6.2: Main results - Average impacts 160

Table 3.6.3: Experience analysis results...167

Table 3.6.4: Experience analysis results - Average impacts......................................169

Table 3.7.1: Bushfire Inquiries of WA...172

Table 3.7.2: Before and after Waroona Fire of 2016 173

Table 3.7.3: Alternative models 176

Table 3.9.1: Alternative models...180

LIST OF FIGURES

CHAPTER 1 THE NEAR-MISS EFFECT OF WILDFIRE DISASTERS

Figure 1.1: Reconstruction of the spread of the Waroona Fire....................................53

Figure 1.2: Map of treated properties 57

Figure 1.3: parallel trends check, 2 km proximity treatment 61

Figure 1.4: parallel trends check, 5 km proximity treatment 62

Figure 1.5: parallel trends check, emergency warning 62

CHAPTER 2 WILDFIRE RISK AND PROPERTY PRICES: A DISCONTINUITY ANALYSIS OF THE INTRODUCTION OF BUSHFIRE PRONE AREA MAPS

Figure 2.1: BPA map first edition and residential properties....................................103

Figure 2.2: Regression discontinuity plot under QSMV bin selection method 111

Figure 2.3: Validation test - Histogram of the score around the cut-off.................... 116

Figure 2.4: Manipulation testing plots 122

CHAPTER 3 FOREST MANAGEMENT PRACTICES AND SAFETY PREFERENCES: DO HOUSEHOLDS WELCOME PRESCRIBED BURNING?

No figures

LIST OF ACRONYMS

ABC	Australian Broadcasting Corporation
AEA	American Economic Association
APM	Australian Property Monitors
ATE	average treatment effect
AUD	Australian dollar(s)
BAL	bushfire attack level
BCA	Building Code of Australia
BFF	The Bushfire Front
BHL	bushfire hazard level
BNHCRC	Bushfire and Natural Hazard Cooperative Research Centre
BPA	bushfire prone area
BPV	bushfire prone vegetation
CAAA	Clean Air Act Amendments
CV	contingent valuation
DBCA	Department for Biodiversity, Conservation, and Attractions
DD	difference-in-differences
DFES	Department of Fire and Emergency Services
DPAW	Department of Parks & Wildlife Service
EU	expected utility
FES	Fire and Emergency Services
GHG	greenhouse gas
GIS	geographic information system
HPF	hedonic price function

HPM	hedonic price method / hedonic price model
HRB	hazard reduction burning
HRS	Hazardous Ranking System
LATE	local average treatment effect
LMZ	land management zone
MSE	mean squared error
MV	mimicking variance
NSW	New South Wales
PH	Perth Hills
QND	Queensland
QS	quantile-spaced
RD	regression discontinuity
RDD	regression discontinuity design
TSPs	total suspended particles
UGB	Urban Growth Boundary
UNEP	United Nations Environment Programme
USFS	United States Forest Service
US	United States of America
USD	United States dollar(s)
VIC	Victoria
VOI	value of information
WA	Western Australia
WTP	willingness to pay / willing to pay
WUI	wildland urban interface

LIST OF UNITS OF MEASUREMENT ABBREVIATIONS

ha	hectare(s)
m	metre(s)
m^2	metre(s) squared
km	kilometre(s)
km^2	kilometres(s) squared

INTRODUCTION

More than 12,000 years ago, we were hunter-gatherers and nomadic. With the agricultural revolution, settlements arose, and so did a life-changing question that chases us until today: Where to live? Where is it safe and convenient? Amongst the many safety threats we face, natural disasters stand out, and wildfires[1] play a leading role. When I started this research, four years ago, the 2019/20 *Black Summer* bushfires in Australia burnt almost 6 million ha of forest (M.Boer, et al., 2020) and shook up the world with the loss of more than one billion animals (Australian Academy of Science, 2020), 35 fatalities, and more than 2,000 houses destroyed (BBC, 2020; Coates, 2020). Just weeks ago, the 2023 Maui wildfires in Hawaii also shook up the world after the touristic town of Lahaina was crumbled to ash and ruins, leaving hundreds of people missing and dead (ABC News, 2023), and flooding the internet with dramatic footage of tourists and residents struggling to escape. And as I began to write these final words, 12 wildfires burn in British Columbia, Canada; the Tiger Island Fire in Louisiana, US continues to spread and is deemed one of the largest in the state's history; and Greece is experiencing the largest wildfire ever recorded in the European Union. Today, just one week before my submission date, Australia is back on the headlines, amid fears that this 2023/24 bushfire season will be deadly due to hot and dry conditions that are only expected to worsen with the coming El Niño in summer. It is also perceived that Australia is unprepared to face this challenge, due, in particular, to an unsuccessful fuel treatment strategy that has left dense *bushlands* untouched and allowed grass to grow rapidly (Turnbull, 2023).

[1] Throughout the thesis, we refer to wildfires as unplanned vegetation fires that burns over grass, forest, or scrub (AIDR, 2023); which, in Australian terminology, is 'bushfires'.

Despite all, the wildland urban interface (WUI) - desirable for its natural amenities, but fraught with wildfire hazard, and already home to half of the world's population - is becoming increasingly populated (Schug, et al., 2023). At the same time, with climate and land-use change, wildfires are expected to become more frequent and intense (UNEP, 2022), leaving populations in the WUI more exposed to wildfire risk (Schug, et al., 2023) and increasing the potential damages to the economy, environment and societies (UNEP, 2022). This is a problem especially relevant for public land managers, who can provide three broad activities: pre-fire risk mitigation (e.g., educating the community, working with the community to create defensible spaces, updating zoning requirements, and undertaking fuel treatment), fire suppression, and post-fire rehabilitation (Simon, et al., 2022).

This thesis touches mainly on policies dedicated to pre-fire risk mitigation and management. According to Simon, et al. (2022), such policies can motivate private risk mitigation actions, such as avoiding risky behaviour. People may, for instance, choose to live in less risky areas. Why then is the WUI becoming increasingly populated? Are we only living in such areas because we are miscalculating wildfire risk? What can the housing market tell us about our safety preferences?

In this thesis, we explore changes and differences in safety preferences, as revealed through the housing market. More specifically – based on Rosen (1974)'s hedonic price method (HPM) that explains property price as a function of utility-bearing attributes specific to the property and its location - we check for the capitalisation of wildfire risk into property prices. The identification of changes in safety preferences or differences in safety preferences across households is the main objective itself. This is a worthy objective because there is a concern that signals on wildfire risk are disregarded instead of serving as wake-up calls. There are at least three critical circumstances in which we can test households' susceptibility to update their risk perception. First, through the occurrence of a disaster; second, through the provision of risk maps; and third, through land management practices designed to limit risk. For each of these circumstances, we can expect property prices to either increase or decrease depending on how the events are interpreted. We present a chapter for each and discuss potential policy implications that are of interest for the reduction of wildfire's socioeconomic costs.

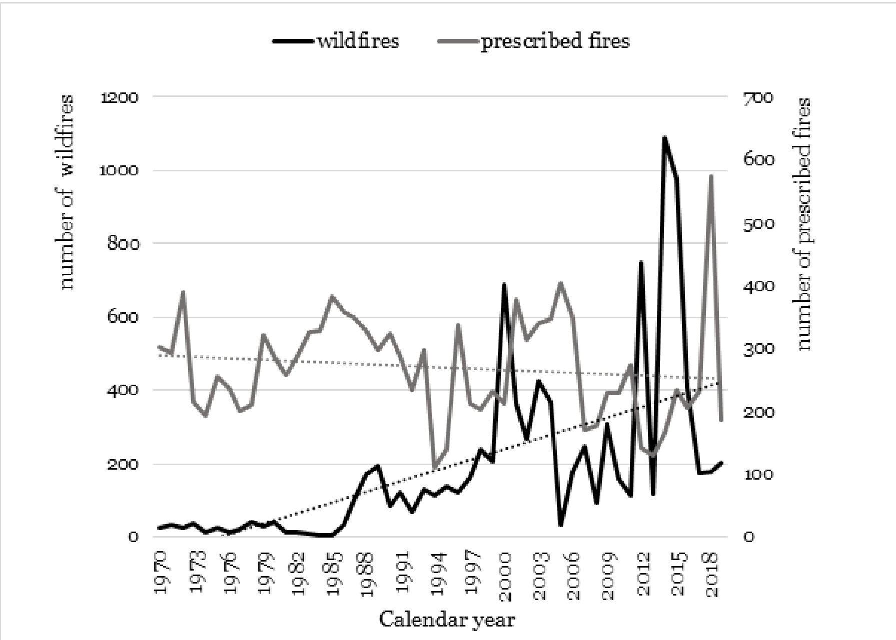
For all chapters, we use the state of Western Australia (WA) as a case study, owing to its large biodiversity value (WABSI, 2023), high wildfire risk, and the use of prescribed burning on private and public land. In particular, forests and woodlands in WA extend to 18 million ha of land (DBCA, 2023), and the south-west forests in particular are important for wildlife habitat and for the provision of ecosystem services, such as water supply for the population in WA, native timber industries, and recreation and tourism activities (DBCA, 2023). Wildfires have been part of the landscape in WA for millions of years and influenced the evolution of plants and animals but represent a real threat for the health of these forests (DBCA, 2023)[2]. The entity in charge of managing wildfire threats is the Department of Biodiversity, Conservations, and Attractions (DBCA).

The most obvious way in which the DBCA mitigates wildfire risk is through prescribed burning, i.e., applying fire to a predetermined area to reduce risk of uncontrollable wildfires, with the target of maintaining 45 percent of fuel at less than six years since

[2] Forests in WA are also threatened by weeds, pests, diseases, land-use disturbances such as land clearing or timber harvesting, and significantly decreasing levels of rainfall, streamflow, and groundwater since the mid-1970s, attributes to climate change (DBCA, 2023).

last burnt (DBCA, 2019)[3]. However, the state of WA has been experiencing a decreasing trend in prescribed fires, while it has been experiencing an increasing trend in wildfires – see **Figure 0.1** below. Since 2010, where our study period begins, the Waroona Fire of 2016 has been the most devastating, resembling only to the 1961 Dwellingup Fires, being both caused by lightning strikes and hot winds (Government of Western Australia, 2016).

Figure 0.1: Wildfire and prescribed fire history in Western Australia



Source: own elaboration, based on the DBCA Fire History (DBCA-060).
Note: wildfires in this figure are those of size greater than 100 ha.

WA has also the fastest growing population in Australia (Steffen, et al., 2015) and hotspots of WUI around south-west forests, which implies that an increasing number

[3] Once a wildfire occurs, however, WA responds with fire suppression and recovery activities. In particular, the main way in which WA responds to wildfires is through the employment of fire management personnel and through keeping infrastructure and equipment in strategic locations across the state. Fire towers, spotter aircrafts, and remote sensing technology are crucial parts of their early detection strategy in order to respond to bushfires in a timely manner. Regarding recovery activities, the DBCA undertakes activities in departmental managed land (DBCA, 2019) This can include restoration of infrastructure (e.g., buildings, septic tanks), clean-ups, disposing of dead animals, etc; and may involve other state and local authorities.

of people are at risk of wildfires (Schug, tbd). We also study WA because of the vast amount of high-quality geographic information system (GIS) data on forested land and fire burn scars that is publicly available, along with other utility-bearing attributes of interest. Consequently, we are surprised by how WA has up to now been overlooked in the academic literature regarding market-revealed safety preferences for wildfire risk. For all chapters, our study period begins in 2010 and ends in 2019. The next paragraphs will briefly explain what we do in each chapter.

In **CHAPTER 1**, we ask: does the near-miss experience generate changes in safety preferences, as reflected by changes in property prices? To answer this question, we study the capitalisation of information effects on wildfire risk updates provoked by a wildfire disaster: the Waroona Fire of 2016, which burnt 69 thousand ha of land, of which 3 thousand were timber forests, leaving 2 fatalities and 181 dwellings destroyed; most of which belonged to the town on Yarloop, which had to be almost entirely reconstructed after the fire. To filter information updates, we study the area that experienced the fire as a near-miss event and exclude the area that experienced it as a direct-hit. We are the first to define the near-miss area by experience, which is multidimensional, and explained by proximity to the burn scar and belonging to areas that received warnings during the fire event. Not all households near the burn scar received warnings. We use difference-in-differences (DD) as an identification strategy to separate out the consequences of mere proximity from the consequences of receiving a warning, making assumptions on the degree of proximity that identifies properties "near" the direct-hit area. Importantly, and perhaps counterintuitively, we propose that wildfire events can have an ambiguous effect on property prices, i.e., prices might increase or decrease after the wildfire. This proposition is however supported by behavioural literature on near-miss events.

In **CHAPTER 2**, we also focus on the capitalisation of information updates on wildfire risk but provoked by the introduction of wildfire risk maps, which intend to clearly inform the public whether or not they live within an area designated as *bushfire prone*. In particular, we study the introduction, in late 2015, of a dichotomous wildfire risk map that is user friendly and publicly available online, i.e., the Bushfire Prone Areas (BPA) map, which displays areas subject to or likely to be subject to wildfire risk - as determined by distance to *bushfire prone* vegetation. The dichotomous mapping design generates a clear boundary that divides treated and non-treated observations, allowing us to implement a sharp spatial regression discontinuity design (RDD) and estimate a local average treatment effect (LATE) that is as good as in a randomised experiment. Since observations in BPAs may be affected by predetermined risk perceptions from the presence of 'risky' vegetation and more stringent planning and building regulation, we undertake further tests to investigate the mechanisms driving our results, and conclude that our estimated LATE, i.e., the BPA effect, is indeed driven by pure information updates and not by these other potential impacts. Our research question in **CHAPTER 2** is therefore as follows: what is the impact of the introduction of wildfire risk maps on safety preferences as reflected by property prices? Is there a price differential that reflects differences in safety preferences across the boundaries of wildfire risk maps?

In **CHAPTER 3**, we ask: is prescribed burning positively valued by households, as reflected by property prices? To answer this question, we study the capitalisation of changes in exposure to prescribed fires - i.e., fires that arise from the practice of prescribed burning, a forest management practice designed to limit the risk of uncontrollable wildfires, but also controversial due to amenity concerns (e.g., biodiversity loss) and concerns of prescribed fire escapes. Based on scientific evidence on fuel age and wildfire risk, and on our previous findings, we define 'exposure' as occurring within the first 6 years prior to sale date and within 5 km from property's location. Importantly, we control for the exposure to wildfires too, which also generate risk reduction and disamenity effects, but in contrast to prescribed fires, are unintended. We anticipate that a positive value could only reflect strong safety preferences.

We believe our findings are relevant to policy makers insofar as they are interested in whether and how people incorporate information related to wildfire risk into their safety preferences. We do this with a backward looking and market revealed preferences approach, i.e., the HPM. We do not, however, study preferences for changes in the level of nonmarket goods not-yet experienced, as can be done with a stated preferences approach.

According to Simon, et al. (2022), estimates from both stated and revealed preference approaches might improve the information available and may be used by wildland fire managers when deciding on the strategies to follow in regard to pre-fire risk mitigation, fire suppression, and post-fire landscape rehabilitation. In particular, the authors suggest that managers may use a value of information (VOI) approach to inform their strategy. The VOI is defined as the "expected gains from making more optimal decisions, as a result of acquiring additional information in the presence of uncertainty" and is expressed as the difference between the valuations of fire management outcomes with and without the improved information (Simon, et al., 2022). It is not the aim of this thesis to contribute to VOI approaches lead by public fire managers. Nor are we making any claims on the value of the information this thesis generates. Nevertheless, our estimates may be of interest to wildland fire managers if the decision-making process requires empirical evidence on if and how information suggestive of wildfire risk generates changes and differences in safety preferences, as revealed by housing choices on where to live.

Please note that my supervisors, Professor David J. Maddison and Assistant Professor Allan Beltran, contributed to the conceptualization and editing of **CHAPTER 1** and **CHAPTER 2** of this thesis. The literature review, data analysis, interpretation and discussion of results, and writing of the aforementioned chapters is my own work.

CHAPTER 1 THE NEAR-MISS EFFECT OF WILDFIRE DISASTERS

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ABSTRACT

Using the hedonic price method, we identify the near-miss effect of the Waroona Fire in Western Australia in 2016. Our strategy for identification relies on the use of difference-in-differences. The dataset includes more than 51,000 property transactions from the Peel and Southwest regions in WA for the period of 2010 to 2019. Compared to existing hedonic analyses of the impact of wildfires, uniquely we distinguish between near-miss areas that received warnings and areas that were merely close to the burn scar. Our findings suggest that the proximity treatment effect is positive, whereas the warning treatment effect is negative. We argue that the proximity treatment effect is an impure near-miss effect that entangles a positive risk reduction effect from burnt fuel and a disamenity impact from, for instance, the burnt landscape.

Keywords: near-miss, wildfires, Australia, hedonic, difference-in-differences

JEL codes: Q23, Q51, Q54

1.1 INTRODUCTION

Forests' presence in our planet is both large and vital. They occupy approximately 30% of the land surface area and provide multiple ecosystem services, which can be marketed or not, such as cultural amenities, food, water, timber, biodiversity conservation, and climate and flood regulation (Prăvălie, 2018).

Australia is home to 134 million hectares (ha) of forest[4], storing nearly 22 thousand million tonnes of carbon (ABARES, 2019). Nearly 16 percent of these forests are located within Western Australia (WA) (ABARES, 2019), a region with a unique biodiversity due to its endemism, i.e., to the fact that some species of flora and fauna are not found anywhere else (WABSI, 2023). Amongst the endemic species that live there more than 10 thousand years ago, are the Albany pitcher plant, honey possum, sunset frog, western swamp tortoise, and assassin spiders (Conservation and Parks Commission, 2022). Not only is WA's biodiversity unique, but also large. For instance, the number of flowering species in WA's Fitzgerald River National Park surpasses that for the entire United Kingdom (WABSI, 2023). In fact, WA is the only region in Australia recognised as a *Global Biodiversity Hotspot*[5] (WABSI, 2023).

Forests in WA contribute to the economy beyond their biodiversity values. For instance, the Department for Biodiversity, Conservation, and Attractions (DBCA) actively promotes recreational activities by providing specific locations to walk, hike, bike, camp, picnic, fish, or canoe (DBCA, 2023). In addition, at the national level, the

[4] The Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) defines forests as tree-dominated areas with tree heights exceeding 2 metres and canopy cover of at least 20%.
[5] These are regions that, despite having lost 70 percent or more of their original habitat, contain at least 1500 vascular plant species (WABSI, 2023).

industries of forestry and forest-product manufacturing contribute to 0.5 percent of the Australian GDP and employ around 76,200 people altogether[6] (ABARES, 2019).

Wildfires put both market and non-market goods and services in danger. In Australia, this is a persistent problem that only seems to be worsening. During the period of 1901-2011, 260 wildfires were recorded and a record of 2060 houses lost on one single day; the 16th of February 1983, baptized as 'Ash Wednesday' (Blanchi, et al., 2014).

Recently, the situation is not necessarily better. The 2019/20 bushfire season had an unprecedented combination of weather conditions, fire intensity, fire behaviour and impact on wildlife and the environment (Australian Academy of Science, 2020) and has been perceived as 'different' and 'terrifying' (Bowers & Mason, 2020). In fact, 5.8 million ha of 'mainly temperate broadleaf forest' were burnt[7] (M.Boer, et al., 2020), 35 lives were lost[8] and approximately 2000 houses were destroyed (The Guardian, 2019; BBC, 2020; Coates, 2020). Moreover, nationwide, one billion animals were killed and 113 animal species were left in danger of extinction, either due to their death or the destruction of their habitat (including native species such as the Koala, the smoky mouse, the Kangaroo Island dunnart, and the Northern corroboree frog) (BBC, 2020).

This event was greatly featured in the media, flaming a political debate around the country's climate change policy. Only between 15th of November 2019 and 17th of February 2020, more than 130 news articles relating to 'bushfires' were published in 'The Guardian' and 'BBC' news altogether. Social media platforms shared a similar reaction, with more than 210,000 posts under the hashtag '*prayforaustralia*' on

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[6] Statistics correspond to reported values for the year of 2017-18.
[7] This is unprecedented because 21% of the Australian temperate broadleaf and mixed forest biome has been burned only during the latest bushfire season; a figure larger than for any other continent in the last 20 years (M.Boer, et al., 2020).
[8] Amounting to 54% of the bushfire related deaths recorded since 2010 (Coates, 2020) .

Instagram[9]. Many of the articles and posts harshly criticised the former Australian Prime Minister Scott Morrison and his *sceptic* approach to climate change[10]; demanding stringent actions to reduce greenhouse gas (GHG) emissions and protect lives and wildlife[11]. This is not surprising considering that Australia's GHG emissions continued to increase since 2015 (Climate Transparency, 2019) whilst hotter and drier[12] seasons (Bureau of Meteorology, 2019) become a new normal[13].

This study informs this debate, albeit in a minor way, by contributing to a better understanding of Australian households' decision-making in relation to wildfires. More specifically, we investigate the change in property prices following a wildfire disaster. The case study we employ is a single, large-scale event that presaged the 2019/20 bushfire season: the Waroona Fire of January 2016 in Western Australia (WA). Because we are interested in information effects that may alter risk perception, we focus on the near-miss properties, i.e., properties whose households experienced the event as a near-miss. For this purpose, we use the hedonic price method (HPM). We determine whether these near-miss effects are positive or negative.

Surprisingly, this study appears the first to examine explicitly the near-miss effect of wildfires in Australia. Apart from the unique geographical domain of its application, our study also makes several other contributions to what is otherwise a United States

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[9] As of 26th of February 2020.
[10] Scott Morrison is widely perceived as a climate change sceptic since denying links between GHG emissions and 'bushfire' risk (The Guardian, 2019).
[11] Australia is ranked as the G20's third country furthest off-track from their agreed emission targets and its current government is criticized for its lack of intentions to determine new renewable energy targets and implement further policies for emission reduction on the transport and industry sectors (Climate Transparency, 2019).
[12] i.e., seasons with higher-than-average temperature and lower-than-average rainfall precipitation.
[13] In fact, between the period of 1980-2019, Australia has been consistently reporting annual mean temperature anomalies above average. Alarmingly, the year of 2019 was the warmest, on average, ever recorded in Australia, with a record high of 41.9 degrees Celsius on the 18th of December (Bureau of Meteorology, n.d.).

(US) based literature. First, unlike most analyses, we adopt a difference-in-differences (DD) identification strategy, allowing us to attribute observed changes in the price of near-miss properties to the Waroona Fire. Second, we use geographic information systems (GIS) software, combined with satellite data, to measure the distance between individual properties and the burn scar left by the Waroona Fire. Third and most important, we incorporate into the analysis spatially distinct warnings issued by the Department of Fire and Emergency Services (DFES) during the actual event. This information comes from the official enquiry that followed the Waroona Fire. This innovation distinguishes our research from a literature that often associates 'near-miss' with physical proximity. Our study by contrast, acknowledges the multidimensional nature of the near-miss effect and the possibility of different near-miss experiences arising out of the same event. Here, the Waroona Fire offers a perfect example. Not all households living in proximity to the fire were targeted by the warnings, and of those who were, some were unaware of these warnings because the communication strategy was not uniform. Because of the scale of the Waroona Fire, not all households in proximity to the resulting burn scar had the same near-miss experience. Some households received warnings because they were in the path of the approaching flames. Other households received no warnings because they were upwind of the wildfire and had a ready means of escape.

We find a positive and significant near-miss effect from proximity to the burn scar. This result differs from the negative near-miss effect of proximity to wildfires mostly found in the US literature. Our explanation is that the price of property in proximity to the burn scar increased because of a reduction in the risk of future wildfires that dominates any disamenity impact. By contrast, properties in locations subject to warnings suffer a price discount. We believe that these warnings triggered a sense of vulnerability.

The remainder of this chapter is as follows. The next section describes previous literature on cognitive biases in the face of risk, behaviour in the face of near-miss events, and studies using the HPM to estimate the near-miss effect of natural disasters on property markets. Section 1.3 explains the methodology employed to estimate the near-miss effect of wildfires on property prices. Section 1.4 describes the Waroona Fire of 2016. Section 1.5 describes our data sources and section 1.6 presents econometric estimates of the near-miss effect. We subject these results to a battery of tests in section 1.7, where we also endeavour to interpret our findings. The final section concludes with some ideas for future research.

1.2 LITERATURE REVIEW

To estimate and interpret the near-miss effect of wildfires we build on a large group of literature focused on risk perception, near-miss experiences, and relevant hedonic applications. The search for this literature involved specific keywords, e.g., "*near miss OR near-miss OR nearmiss AND hedonic*", and the use of FindIt@Bham, the University of Birmingham's search engine, which includes the Econlit database. To ensure the inclusion of high-quality literature and relevant studies, we conducted additional searches restricted to 3 - 4* ranked journals[14] and journals specialized in environmental, natural resource, and regional economics, or risk and uncertainty, regardless of their ranking. Each search is identified by a letter and a number. For example, all searches related to the near-miss phenomenon of natural disasters are

[14] Star ranking is that of the 2018 Academic Journal Guide developed by the Chartered Association of Business Schools (CABS).

identified by the letter G and six searches, namely 'G1', ..., 'G6', were conducted for this purpose. Additionally, we searched the Bushfire & Natural Hazards Cooperative Research Centre (BNHCRC)'s 'Value Tool for Natural Hazards' database for studies that value environmental attributes in Australia[15]. As a result, more than 300 relevant references were sourced from 'FindIt@Bham' search engine (see **Table 1.2.1** below). However, 78 and 21 additional relevant literature were sourced from selected references and from news articles, respectively – giving a total of 406 relevant sources of information. The literature reviewed in this section and cited throughout this chapter corresponds to the final selection following a read of the abstracts.

Table 1.2.1: Literature review search

	Search topic	**Total entries**	**Selected entries**
A	Hedonic pricing in Australia	1151	42
B	Hedonic pricing methodology	345	50
C	Climate change and wildfires	99	64
D	Forest fires in Australia	115	89
F	Economic analysis of wildfires	113	22
G	Near-miss and natural hazards	160	32
H	Forest ecosystems	10	1
I	Availability heuristics	222	31
	TOTAL	2215	331

Critical to the understanding of the near-miss effect, is the literature on cognitive biases and the behavioural literature on near-miss events.

According to Kahneman (2011), people employ two thinking systems when forming conclusions: 'fast' and 'slow'. Fast thinking relies heavily on intuition and emotions, whilst slow thinking relies on logic (Bray, et al., 2015).

[15] The Value Tool for Natural Hazards intends to facilitate policy making on natural hazard management and its database contains research centred around health, environmental and social value estimations (BNHCRC, n.d.).

The slow-thinking system requires reasoning and effort to reach conclusions. For example, Bayesian reasoning relies on questioning our prior beliefs to recalculate likelihoods (Kahneman, 2011). The fast-thinking system provides fast answers through the use of inferential rules known as 'heuristics' (Slovic, et al., 1982; Shleifer, 2012), which, in turn, give rise to systematic errors in the assessments of probabilities, known as 'cognitive biases' (Tversky & Kahneman, 1974).

There is evidence that suggests high consequence and low probability events increase perceived risk due to their "attention-focusing effect", e.g., Hansen, et al. (2006) (Kousky, 2010, p. 398). This type of events demand the use of heuristics to assess risk.

One of such heuristics is 'availability heuristics', which is present when people judge the probability of an event by the "ease with which instances or occurrences can be brought to mind" (Tversky & Kahneman, 1974, p. 1127). Availability bias is therefore present when people mistakenly judge an event as either more or less likely than it is, simply because they rely on the easiness by which the event 'comes to mind'[16]. Instances which are more familiar, salient, or recent, are easier to retrieve, but not necessarily more likely to occur. Availability heuristics may be at least partially explained by 'affect' heuristics, i.e., a mental shortcut where risk is predominantly perceived as feelings (Slovic, et al., 2004). Risks of high emotional charge are overestimated, and vice versa (Lichtenstein, et al., 1978).

Risk perceptions may be amplified, or attenuated, through social processes. For instance, through news media. Kasperson, et al. (1988) name this process "the social amplification of risk". The authors suggest that the risk event initiates signals on those

[16] The event may 'come to mind' by either retrieval, construction, or association (Tversky & Kahneman, 1974). Given that we study near-miss events, retrieval is most relevant for this study.

who directly experience the event or those who simply received information regarding the event. Then, these signals are decoded by transmitter and receiver in such a way that some are intensified whilst others are attenuated, and some are discarded whilst others are preserved for interpretation. Using survey data, Brenkert-Smith, et al. (2013) study the social amplification of wildfire risk in Colorado, US, and find evidence of the social amplification of risk for perceptions of probability, but not of consequence. Their findings suggest that information sources and social interaction can alter perceived frequency of wildfires, but not perceived consequence. Additionally, the authors find that the role of mass media in shaping risk perceptions is quite limited, compared to social informal interactions, such as fire-related chats with neighbours, attending fire-related events, or noticing the density of vegetation of neighbouring properties.

Households may fall into what Kates (1962) denominates 'the prison of experience' dilemma. Without repeated experience, Kates (1962) suggests, some floodplain managers are discouraged to seek further alternatives because the experience is "not so bad after all", whilst some other managers are encouraged to believe that nature has delivered what it "had in store for them" and, therefore, the experience will not repeat for some time (p. 140)[17].

For instance, near-miss events may be interpreted differently depending on the household's experience. Tinsley, et al. (2012) classify near-misses into two categories: vulnerable and resilient. Vulnerable near-misses display information that highlights vulnerability in face of a natural disaster, encouraging its interpretation as a disaster

[17] This is particularly important for our research, as wildfires burn fuel, and therefore, reduce the likelihood of future wildfires, i.e., wildfires generate risk reduction effects in the affected area.

that ‘almost happened’; whereas resilient near-misses do not display information on the potential harm that could have been inflicted, encouraging the near-miss to be interpreted as a disaster that ‘did not occur’. For example, households that live in hurricane-prone areas but who never had any property damage, nor their neighbours, possess resilient near-miss information; whereas households whose neighbours experienced a tree fell on their car that could have caused serious injuries if anyone where inside, possess vulnerable near-miss information.

According to Tinsley, et al. (2012), households with vulnerable near-miss information are more likely to mitigate risk than households with resilient near-miss information. However, the authors suggest that, because households escape harm, near-misses are more likely to be interpreted as resilient experiences. Moreover, the authors build on Kahneman & Miller (1986)’s norm theory to suggest that near-misses, resilient or not, favour lower risk perception than direct-hits do, and therefore, hinder mitigation behaviour.

Similarly to Tinsley, et al. (2012), Dillon, et al. (2014) suggest risk perception is lower for individuals with resilient near-miss information, preventing them from assuming mitigation behaviour in face of future hazardous situations. According to Dillon, et al. (2014), households with resilient near-miss information are more likely to suffer from outcome bias, i.e., when confronted with a near-miss experience that highlights resiliency, the household focus on the successful outcome and ignores the process that paved the way to it (Baron & Hershey, 1988). The authors also suggest that outcome and availability bias work together, i.e., the relevant instance that *comes to mind* is the outcome of the past event. A similar conclusion to that of Dillon & Tinsley (2008), who propose near-misses – resilient or not - are judged as if they were successes because of their favourable outcome, despite chance being the sole element preventing damage.

Outcome bias may, however, be counteracted. Dillon & Tinsley (2016) find that risk communication that highlights vulnerability may counteract the optimistic feelings in those who possess resilient near-miss information by the means of altering perceived probabilities upwards.

We now continue the literature review with studies using the HPM to identify changes in property prices associated with wildfire events. Perhaps most relevant to our research because it involves Australia is Athukorala et al. (2016) who conduct a before-and-after analysis of the impact of wildfires (and floods) on property values in Rockhampton, Queensland. Although the authors do not explicitly investigate the near-miss effect, they nevertheless compare (i) a suburb directly affected by the so-called Black Saturday bushfires, (ii) a suburb directly affected by a December 2010 through January 2011 flood event and (iii) an adjacent suburb, “largely unaffected” by either event. Athukorala et al. (2016) find that the largely unaffected suburb experienced an increase in house prices of 7.98% for the year 2011, significant at the 20 percent level. However, a significant weakness in this study lies in the identification strategy, specifically the inability to separate the general downturn in house prices caused by the contemporaneous sub-prime lending crisis, the inability to disentangle forested areas from the source and final boundaries of the fire, the use of partially affected suburbs as control group, and the lack of an impact evaluation approach – as that of DD.

Turning now to the US literature on wildfires, Loomis (2004) states that households living in forested areas consider both wildfire risk and amenity values. He argues that the perceived net benefits must decline after a near-miss wildfire event, via an increased perception of the risk. To test this, he studies the impact of a major wildfire on the housing market of a near-miss area. The wildfire event is the 1996 Buffalo Creek fire in Colorado, which 2 months later was hit by a severe flash flood that closed the main highway and destroyed the town's water treatment system. The near-miss area is the town of Pine, 2 miles away from the fire. To capture the impact of the fire on property prices, the empirical specification includes a 'post-fire' dummy, which takes the value of unity if the sale took place after the fire[18]. On average, properties sold after the Buffalo Creek fire were subject to a 15-16% price discount. Critically, the author uses a continuous date variable to explain the underlying trend in house prices.

Mueller and Loomis (2008) estimate the impact of repeated wildfire events on the housing markets of Riverside and Orange counties in Los Angeles. In particular, they consider the impact of two small wildfire events – Fires A[19] and B[20], which took place in 1991 and 1995 respectively, and burned 379 and 331 ha respectively[21]. 2,250 properties, all of which were within 1.75 miles of the fire areas, were sold either (i) before either fire, (ii) after one fire or (iii) or after both fires. Forest fire dummies capturing the near-miss impact of the wildfires suggest properties sold with a price discount of 19.7% after 1 fire event and a further 12.9% after both fire events.

[18] It should be noted that the author considers the 60-day time period usually applied in real-estate transactions in the study area, i.e., the 'post-fire' dummy takes the value of unity for all sales taking place 60 days after the 'Buffalo Creek' fire or later. During the 60-day period, loan approval, appraisal and inspection usually takes place.

[19] These include the Sylmar and Polk fires, which took place only three days and a few miles apart from each other.

[20] This includes the Towseley fire.

[21] The authors also consider a third fire in their sampling: Fire C which took place in 1997 and burnt 977 acres (395 ha). However, because only 34 properties were sold after Fire C, they decide to disregard the impact of the third fire. Fire C constitutes the Placerita and Sierra fires, which took place 40 days and a few miles apart from each other.

The wildfire events are studied by Mueller et al. (2009) using the same 2,250 observations. This time however, the model specifies the environmental attributes of the property in detail. The authors include distance to the nearest edge of US Department of Agriculture Forest, as well as number of days elapsed since (both) first and second fire events. The authors analyse progressive 0.5-mile cut-offs (up to 1.5 miles). The results vary greatly depending on the cut-off, with the third 0.5-mile cut-off yielding the largest near-miss effect. The model does not control for time trends in house prices.

Aiming to test for a differential near-miss effect across the housing price distribution[22], Mueller and Loomis (2014) estimate a hedonic price function using quantile regression. Using the same data (and empirical specification) as Mueller and Loomis (2008), they find a strong differential impact across the housing price distribution. The negative price impact is strongest for properties in the upper price quartile.

Hansen and Naughton (2013) study the impact on property prices of repeated wildfire events (and spruce bark beetle [SBB] outbreaks)[23] observed during 1990-2010 in the Kenai Peninsula, Alaska. Thirty-three large (>3.3 ha) and 1,160 small (<3.3 ha) wildfire events are considered. They consider 0-0.1, 0.1-0.5 and 0.5-1km rings. Unusually, the dependent variable is assessed market value rather than sale price. Uniquely, their findings suggest large wildfire events increase assessed property values for all distance rings. The authors provide various explanations for these findings e.g., enhanced environmental amenities, such as improved views of the ocean and mountains, and

[22] Note that the authors do not refer to a near-miss effect, the wording is ours.
[23] SBB outbreaks include a) one massive outbreak beginning in 1989 and fading in early 2000's; and b) isolated outbreaks since (a) faded. According to data from Kenai Peninsula Borough cited by the authors, the white spruce species on the western side of the peninsula endured an average of 66 wildfire events per year since 1990, amounting to 60,000 ha of which the 2007 Caribou Hills fire stands out for destroying 88 homes and cabins plus 109 outbuildings.

improved hiking trails – which may overcome any disamenities from burnt areas. Another possible explanation is a decrease in the risk of future wildfires.

Kiel and Matheson (2018) study the impact of the September 2010 Fourmile Canyon fire in Colorado, US, on the sale price of houses in Boulder County by implementing the HPM using a DD approach. The authors use a dataset consisting of 9,360 properties covering the period of January 2009 to April 2012. Additionally, they control for the level of risk according to the area in which the house is located, as rated by the Boulder County website, which is accessible to homebuyers. The authors find a price discount of 21.7% for houses located in the very high-risk area after the fire, compared to those located in the low-risk area. To account for changed amenity levels, the authors implement a second set of regressions where they include a dummy variable to identify houses within 0.8 km of the fire perimeter. Results suggest that the impact is driven by changes in risk rather than changes in forest amenity levels.

McCoy and Walsh (2018) study the housing price impact of wildfires occurring in the Colorado Front Range in 2000-2012. In order to implement their DD identification strategy, the authors define three different treatment and control groups. The first treatment is based on proximity, where properties in the treatment group lie within 2km of the burn scar. The second treatment includes properties with a view of the burn scar according to the outcome of a GIS viewshed analysis. The third treatment is according to the Wildfire Threat Index, which takes the values of 1 to 5. The results for the proximity analysis suggest an immediate price discount of 12.6% for the properties sold after the fire. For the view of the burn scar treatment, the authors detect a 6.4% price discount in year 1, and this impact persists (and indeed increases) for years 2 and 3 after the fire. Finally, the analysis on the Wildfire Threat Index suggests a discount of 9.4% for properties in high-risk areas compared to those in the lowest risk category. However, the impact is short-lived and insignificant only 2 years after the fire.

In sum, the empirical literature of wildfire near-miss events is based mainly in the US and, apart from the somewhat unusual paper of Hansen and Naughton (2013), suggests the near-miss effect from proximity to the burn scar is negative. This negative near-miss effect may result from two forces: reduced amenity values and a heightened perception of wildfire risks.

Only recently has the empirical near-miss literature for wildfires adopted a quasi-experimental approach to identification in an effort to ensure that the near-miss impacts on property prices are causally attributable to the wildfire event. Only a minority of papers accurately measure the distance from the property to the burn scar and some combine wildfire events with other impacts such as those arising from floods or insect infestations. None deals with a wildfire event of the scale of the Waroona Fire. Critically for our purposes, there is a clear omission of the information effect that arises from receiving warnings during the fire event, such as those issued by the DFES during the Waroona Fire. This omission is present for the conceptualization of the near-miss effect and for its estimation.

On the other hand, the HPM literature on the near-miss effect of other natural hazards is much more developed. Several studies adopt an impact evaluation approach through the identification of treated (near-miss) and non-treated (non near-miss) properties in the study area, e.g., Hallstrom & Smith (2005), Carbone, et al. (2006), Atreya & Ferreira (2015), Hennighausen & Suter (2020), and Beltran, et al. (2020) for floods and hurricanes, and Naoi, et al. (2009) for earthquakes.

Evidence on the near-miss effect of floods and hurricanes is mixed. Some studies find negative, whereas other find positive or zero, near-miss effects. For instance, Hallstrom & Smith (2005) and Carbone, et al. (2006) find a negative near-miss effect. The authors study the impact of the 1992 hurricane *Andrew* on property prices in two counties: Lee, which nearly missed the hurricane, and Dade, directly hit; both in Florida, US. As estimation strategy, both studies use DD and repeat-sales observations. Hallstrom & Smith (2005) find a negative near-miss effect of 19% for the Lee county, whereas Carbone, et al. (2006) find a negative near-miss effect of 23-26%.

Atreya & Ferreira (2015) and Hennighausen & Suter (2020) study large flood events and find no significant evidence of a near-miss effect. Atreya & Ferreira (2015) study a major flood event provoked by the tropical storm *Alberto* in 1994 in the city of Albany, located in the county of Dougherty in Georgia, US. The authors use inundation and floodplain maps and GIS parcel data to clearly distinguish properties subject to inundation effects from those subject to information effects only, and implement a DD. Their findings suggest only the inundation effect, and not the information effect, is capitalized into property prices, and that inundated properties mapped within floodplains are most affected. In particular, inundated properties within floodplains experienced a price discount of 48%, whilst those outside floodplains experienced a price discount of 36%.

Similarly, Hennighausen & Suter (2020) use inundation and floodplain maps to study the 2013 Colorado floods in Boulder County, Colorado, US. The authors implement a triple DD to explore whether floodplain maps generate information effects, and whether inundation makes a difference. Their findings suggest both floodplain maps and flooding extents are important for the identification of changes in property price.

Prior to the flood, properties within the floodplain were sold at a 6.5% discount, compared to those outside[24]. However, after the flood, properties within the floodplain experienced no significant price change. When discerning between inundated and non-inundated properties, the authors find a 21% price discount for inundated properties within the floodplain, but no impact for inundated properties outside. On the other hand, non-inundated properties within the floodplain, i.e., near-miss properties, experienced a price increase, but with no statistically significant marginal effects. The absence of a significant near-miss effect might be explained by the availability heuristics which might operate with direct experience only (Atreya & Ferreira, 2015; Hennighausen & Suter, 2020), or by Bayesian learning if flooding extents represent true differences in risk (Hennighausen & Suter, 2020).

Beltran, et al. (2020), on the other hand, do not study a particular event, but study all inland and coastal floods recorded in England between 1995 and 2014. With the use of high-resolution GIS data, the authors identify near-miss properties as those adjacent to postcodes with any degree of flooding experience. Using DD, the authors find evidence of low persistence near-miss effects, negatively signed for inland floods (-4.0%) whilst positively signed for coastal floods (+4.4%). Beltran, et al. (2020) suggest that coastal households may be interpreting the event as a 'resilient' near-miss.

Naoi, et al. (2009) use nation-wide data to estimate the near-miss effect of massive earthquake events in Japan between 2004-2007. Using earthquake risk measures provided by the government and DD, the authors find that, after a massive earthquake, a 0.2% increase in the annual probability of an earthquake leads to a price decrease of

[24] Importantly, in the Boulder County, properties within the floodplain are required to obtain insurance against floods, which may explain this price discount.

13% and 16% of property values and rental prices, respectively, for near-miss properties.

Finally, to be certain of the originality of our study, we review HPM applications that focus on WA or any of the other three states in Australia, i.e., Queensland (QND), New South Wales (NSW), and Victoria (VIC). These studies amount to a total of 13 – see **Table 1.2.2** below for a list of these studies by location and the attributes valued.

Table 1.2.2: HPM applications for Australia

#	Location	Journal Article	Attribute(s) for valuation
1	WA, Perth	Tapsuwan, et al. (2009)	urban wetland
2	WA, Perth	Zhang, et al. (2014)	rainwater tanks
3	WA, Perth	Ma, et al. (2015)	residential solar photovoltaic systems
4	WA, Perth	Pandit, et al. (2013)	urban tree canopy cover
5	QND, Mount Isa city	Neelawala, et al. (2013)	mining and smelting activities
6	QND, Brisbane	Warren, et al. (2017)	historic districts
7	QND, Brisbane	Plant, et al. (2017)	footpath tree canopy cover
8	QND, Brisbane	Rajapaksa, et al. (2018)	cell phone towers
9	QND, Brisbane	Athukorala, et al. (2019)	wildfire risk
10	QND, Rockhampton	Athukorala, et al. (2016)	wildfire risk and flood risk
11	NSW	Tapsuwan, et al. (2015)	Barmah–Millewa forest and in stream riverflows
12	VIC, North Central Victoria	Polyakov, et al. (2015)	native vegetation
13	VIC	Tapsuwan, et al. (2015)	Barmah–Millewa forest and in stream riverflows

Athukorala et al. (2016) and Athukorala et al. (2019) are the only two HPM applications on wildfire risk, both for the state of QND. We have already described the study of Athukorala et al. (2016) amongst other near-miss studies. In Athukorala et al. (2019), the focus is not on wildfire events, but rather on areas mapped as bushfire prone, i.e., BPAs, by the state of QND. All properties sampled are within 850 m of BPAs. The authors find that distance to BPA is negatively valued. Athukorala et al. (2019) attribute this finding to the high amenity value of BPAs, which include forested areas, meaning that households are willing to pay (WTP) a premium to live near green spaces despite the implicit wildfire risk. However, the authors do not follow a quasi-experimental approach and findings here contradict our results in **CHAPTER 2**, where we find that properties within BPAs are sold at a price discount compared to those in non-BPAs.

Other studies on Australia also suggest that green space is positively valued. Pandit, et al (2013) study the impact of tree canopy cover on residential property prices in Perth, WA, and find that tree canopy cover is positively valued, but only if located in adjacent public space. If located within 20 m of the property, tree canopy cover is negatively valued. The authors suggest that management and opportunity costs for trees on private property exceed benefits, whereas urban tree planting public programs do not. Similarly, Plant, et al. (2017) find that footpath tree canopy cover is positively valued within 100 metres of the property and that, therefore, 2031 target levels would provide benefits that justify the costs of taxes. Polyakov, et al. (2015) find evidence that suggests that current levels of native vegetation could be increased to maximize private benefits. Interestingly, Pandit, et al (2013), Plant, et al. (2017) and Polyakov, et al. (2015) do not discuss the relationship between green spaces and wildfire risk, as do Athukorala et al. (2019).

Besides green spaces, HPM applications on Australia suggest households positively value water ecosystems, such as urban wetlands (Tapsuwan, et al., 2009) and the Barmah–Millewa forest and in stream river flows (Tapsuwan, et al., 2015).

We do not review the remaining studies listed in **Table 1.2.2** because they are not relevant for our study.

1.3 METHODOLOGY

1.3.1 THE HEDONIC PRICE METHOD

To estimate property prices, we rely on the hedonic price function (HPF). The HPF was first characterized by Rosen (1974) based on Kevin Lancaster (1966)'s *new approach to consumer theory* in which goods are conceptualized as bundles of attributes that, when consumed, give rise to utility.

The HPF emerges from the hedonic price model (HPM). This is a model of product differentiation: it recognizes the heterogenous nature of goods in terms of their embedded 'utility-bearing' attributes – simply 'attributes' from this point forward. Moreover, It provides a method for matching buyers and sellers of implicit markets, allowing to estimate implicit market prices of the attributes embedded on goods, for which no explicit market exists (Greenstone, 2017), i.e., there is an implicit market for attributes of heterogeneous goods, for which consumers pay implicit prices. Since consumers are heterogeneous, these exhibit heterogeneity in the willingness to pay (WTP) for different levels of a particular attribute under a constant level of utility (Rosen, 1974; Greenstone, 2017). Importantly, estimating the WTP for the implicit attributes, allows to assess welfare implications from marginal changes in the levels of attributes traded in implicit markets and conveyed through housing choices

(Kuminoff, et al., 2010). Given that virtually all goods are heterogeneous in attributes, the HPM revolutionized the way we think about several fields of economics - such as labour, public, urban, and environmental economics, where jobs, cities, and houses are all goods of multiple attributes (Greenstone, 2017)[25].

They key assumption underpinning the HPM so that estimated implicit prices reflect households' true preferences for the attributes of interest is that the housing market is in equilibrium, i.e., homebuyers and sellers' maximizing behaviour leads to market clearing conditions. The equilibrium is such that, at the location chosen by homebuyers, amounts of attributes supplied by sellers must equal amounts demanded by consumers, and no buyer or seller can improve their position (Rosen, 1974, p. 35)[26].

For this assumption to hold, four other conditions must be met. First, that homebuyers and sellers have perfect information on price P and attributes $\boldsymbol{Z} = (z_1, z_2, \dots, z_n)$ of the housing market, i.e., the objective assessment of the spatial landscape of the market is shared by both homebuyers and sellers (Kuminoff, et al., 2013, p. 1013). Second, that

[25] Some examples in environmental economics include estimates for valuation of air quality (Smith & Ju-Chin Huang, 1995; Chay & Greenstone, 2005; Kim, et al., 2003; Brookshire, et al., 1982), avoidance of hazardous waste sites (McCluskey & Rausser, 2003), avoidance of noise pollution (Pope, 2008), and water pollution (Leggett & Bockstael, 2000).

[26] Market equilibrium for a given attribute z_j results from the tangencies of bid and offer functions of homebuyers and sellers, respectively – where bid functions reveal homebuyers' maximum WTP for different levels of attribute z_j at a given level of utility, and offer functions reveal sellers' reservation price for different levels of attribute z_j at a given level of profit (Rosen, 1974, pp. 39, 42) (Greenstone, 2017, pp. 1892 - 1894). The interaction – or "kiss" - between homebuyers' bid and offer functions generates the hedonic price schedule (HPS), a locus between house prices and a given attribute z_j – the envelope (Greenstone, 2017, p. 1892) (Rosen, 1974, pp. 40, 44). At each point in the HPS, there is a homebuyer whose marginal WTP equals a seller's marginal cost of production, and both values equal the marginal price of attribute z_j. Importantly, the HPS reveals the price that allocates homebuyers across locations and levels of attribute of interest z_j. Welfare gains or losses can be inferred for marginal changes along the locus. There is a trade-off between quality level of attributes of interest and housing price, e.g., households living in areas of poor air quality are compensated with lower housing prices (Greenstone, 2017, p. 1894). Therefore, under market equilibrium conditions, the estimated implicit prices of attributes of interest can be interpreted as a welfare measure.

if a household is out of equilibrium, they can move to a more preferred location with no transaction costs, i.e., there is free mobility (Bayer, et al., 2009). Third, that both homebuyers and sellers belong to a single market, i.e., no market segmentation (Palmquist, 2005). Finally, it is assumed that the level of attributes varies continuously across time and space, i.e., levels do not vary discretely, and households consume attributes in continuous quantities (Kuminoff, et al., 2013). This implies differentiable utility and cost functions[27].

The use of the HPM is, however, of limited validity. There are occasions in which estimates may be biased. For instance, attenuation bias is a threat when information is not perfect (Pope, 2008) and when there is no free mobility (Bayer, et al., 2009). These are real threats, as there is empirical evidence on information asymmetries between buyers and sellers, e.g., Schulze, et al (1986), and empirical evidence on high financial and emotional moving costs that prevent free mobility, e.g. Bayer, et al (2009). Additionally, estimates may be biased if the market is segmented (Michaels & Smith, 1990); particularly if segments of the market do not overlap for different consumers (Palmquist, 2005). Other issues to consider when applying the HPM are omitted variable bias and multicollinearity.

Omitted variable bias is a major concern for accurate estimation of implicit price of attribute of interest z_j. The issue arises when attribute z_k has a significant impact on house price P but is omitted on the HPF specification and is therefore included on the

[27] This assumption is implicit in the utility and profit maximization problems for the homebuyer and seller, respectively (Kuminoff, et al., 2013) . For instance, solving for the first order condition (FOC) of the utility maximization problem gives a level of attribute of interest z_j such that its marginal implicit price equals marginal WTP for an additional unit of z_j, which in turn implies that utility functions are differentiable. If at least one attribute is discrete, solving for the FOC will not yield equilibrium behaviour and there will be no “specific link” marginal price and marginal WTP (Kuminoff, et al., 2013, pp. 1022-1023).

error term. Previous research suggests that, if the threat of omitted variable bias is high, linear Box-Cox, or even simpler functional forms, such as linear or log-linear are preferred for the HPF (Cropper, et al., 1988; Palmquist, 2005).

Spatial correlation can also be an issue in the estimation of implicit marginal prices, especially in the presence of omitted variable bias, because these share similar values across neighbouring properties, i.e., there is a pattern of spatial correlation between prices, neighbourhood attributes and amenities (Kuminoff, et al., 2010).

Multicollinearity arises, for instance, when variations in levels of attribute z_k are correlated with variations in levels of attribute of interest z_j (Kuminoff, et al., 2010), and both attributes are present in the HPF, e.g., air pollution is correlated with unobservable local characteristics related to economic activity (Bayer, et al., 2009), which may give rise to perverse positive signs between air pollution and house prices (Smith & Ju-Chin Huang, 1995; Chay & Greenstone, 2005). Additionally, distance effects – usually used to account for perceived risk - may suffer from multicollinearity, e.g., odour disamenities from two different sources of pollution included separately in the model would give rise to multicollinearity (Cameron, 2006).

The hedonic price method extended for wildfire risk

In this section, we present an extended version of the HPM where changes in wildfire risk perceptions are explained by information updates, giving rise to changes in housing preferences and property prices. For this extended model, and because homebuyers choose a level of self-insurance when deciding where to live (Brookshire, et al., 1985), we follow the EU framework for the consumers' utility maximisation problem, as is usual when studying the incentives for insurance take-up (Ehrlich &

Becker, 1972, p. 623). The characterization of our model is inspired by and heavily reliant on that of Carbone, et al. (2006) for hurricane risk.

As already noted above, each property embodies a unique bundle of attributes $\boldsymbol{Z}$. Given that $\boldsymbol{Z}$ is specific to a property with a unique location, attributes are experienced within the spatial context of the property.

The attribute of interest in this extended model is real wildfire risk π, which is part of $\boldsymbol{Z}$. However, π is unknown, i.e., true probability of wildfire, free from misinformation or measurement error[28] is unknown. Instead, the household is subject to a set of information i regarding wildfire risk, which may include estimates of π, denoted here as $\tilde{\pi}$. The household is also exposed to risk moderating characteristics r, specific to the property, that impact wildfire risk[29]. Therefore, the subjective assessment on wildfire probability p depends on both i and r – see equation **(A)** below. Notice that although p, $\tilde{\pi}$ and π are conceptually different, any of these might be equal by chance.

$$p = p(i, r) \qquad \textbf{A}$$

The price of each property is a function of its embedded attributes ($\boldsymbol{Z}$), wildfire risk moderating characteristics (r), and the corresponding perceived probability of wildfire (p) – see equation **(B)** below. In other words, the price of any property depends upon

[28] Misinformation and/or measurement errors may arise if, for instance, data collected is not accurate (e.g., data accuracy on fire extent, intensity, fuel age, etc., may vary across time depending on available data collection techniques). Also, risk assessments may vary depending on the methodology employed. Moreover, climate change is a new unknown on the determinants of wildfire risk. Furthermore, in Australia, variability on the impact of 'El Niño' phenomenon on fire weather is challenging the diagnosis of divergence between anthropogenic and "natural forcing" signals (Jones, et al., 2020). This might explain why formal attributions to climate change for the unprecedented scale of 2019/20 bushfire season were not made (Smith, et al., 2020).

[29] Such as the flammability of a property's construction materials, elevation, distance to nearest fire station or 'safe area' (e.g., ocean), etc.

the quantities of attributes that it embodies (Palmquist, 2005, p. 559), which are never identical to any other property because each occupies a unique piece of land that offers marginal differences from its neighbours. Given **(A)**, the HPF is specified as in equation **(C)**:

$$HPF: \quad P = P(\boldsymbol{Z}, r, p) \qquad \textbf{B}$$

$$HPF: \quad P = P(\boldsymbol{Z}, r, p(i, r)) \qquad \textbf{C}$$

Under the EU framework, utility functions - which depend on attribute levels $\boldsymbol{Z}$, risk-moderating characteristics r, and consumption of all other goods C - are state-dependent on fire state F or non-fire state NF. In other words, experienced utility level is U^F when a wildfire occurs and U^{NF} in absence of wildfire occurrence, with probabilities p and $(1-p)$, respectively – see equation **(D)** below.

$$EU = p(i, r) \times U^F[\boldsymbol{Z}, r, C] + (1 - p(i, r)) \times U^{NF}[\boldsymbol{Z}, r, C] \qquad \textbf{D}$$

The household maximizes EU by choosing property h^*, subject to prevailing prices P_h, where $h = 1, \ldots, H$, and H is the total number of properties available for purchase and belonging to the same temporal and geographical market. The maximization problem is subject to a state-dependent budget constraint M, where $L(r)$ is magnitude of loss as a function of risk-moderating characteristics r, equal to zero in absence of wildfire occurrence and $\epsilon\,[0, \bar{S}]$ in presence of wildfire occurrence; $\bar{S}$ being the cost of rebuilding entire property – see equation **(E)** below[30].

[30] Note that $L(r)$ can take the value of zero even in presence of wildfire occurrence. This is the case for near-miss properties.

$$M = \begin{cases} P(\mathbf{Z}, r, p(i, r)) + C + L(r) & if\ F \\ P(\mathbf{Z}, r, p(i, r)) + C & if\ NF \end{cases} \qquad \textbf{E}$$

Prior to the wildfire event, households subject to π greater than zero, are unaware of wildfire outcomes, i.e., unaware of the magnitude of loss $L(r)$. This changes once a wildfire occurs. During and after the wildfire, authorities and households receive an exogenous change in set of information i. With i, authorities are empowered to update their objective assessments of wildfire risk $\tilde{\pi}$ and households are empowered to update their subjective assessments on probability of wildfire p. A change in i would cause a change in p equal or different to zero if households choose to maintain or update their beliefs on wildfire risk, respectively. Moreover, a change in p equal or different to zero would cause a change in property price P equal or different to zero, respectively - see equations **(F)**, **(G)**, and **(H)**:

$$\Delta p \begin{cases} = 0, if \Delta i = 0 \\ \neq 0, if \Delta i \neq 0 \end{cases} \qquad \textbf{F}$$

$$\partial p / \partial i \begin{cases} = 0\ if\ \Delta p = 0 \\ \neq 0\ if\ \Delta p \neq 0 \end{cases} \qquad \textbf{G}$$

$$\partial P / \partial i \begin{cases} = 0\ if\ \partial p / \partial i = 0 \\ \neq 0\ if\ \partial p / \partial i \neq 0 \end{cases} \qquad \textbf{H}$$

Due to the updates of the information set and subjective probability of wildfire $\partial p / \partial i$, the household maximizes EU subject to a budget constraint M dependent on state F.

Solving for $\partial P/\partial i$, we get the impact of an exogenous change in set of information i provoked by the occurrence of a wildfire:

$$\left(\frac{\partial P}{\partial i}\right) = \left(\frac{\partial p}{\partial i}\right) \times \left[\frac{U^F - U^{NF}}{p(i,r) \times \left(\frac{\partial U^F}{\partial C}\right) + \left(1 - p(i,r)\right) \times \left(\frac{\partial U^{NF}}{\partial C}\right)}\right] \qquad \textbf{I}$$

In **(I),** the change in subjective probability of wildfires due to an information update $\left(\frac{\partial p}{\partial i}\right)$ is multiplied by the change in experienced utility from a state transition $(U^F - U^{NF})$ as a proportion of the change in EU given a change in consumption. Simply put, wildfire events update the set of information on wildfire risk, bringing about changes in property prices explained by changes in wildfire risk perceptions and scaled by the magnitude to which experienced utility resembles EU when transitioning from a non-fire to a fire state.

Following Tinsley, et al (2012)'s suggestion that near-misses can be interpreted either as vulnerable or resilient events, we propose that the set of information i can have an ambiguous effect on p and hence on property prices, i.e., the wildfire event may generate either an increase or decrease in the sale price of near-miss properties.

1.3.2 DIFFERENCE-IN-DIFFERENCES AS IDENTIFICATION STRATEGY

Besides the HPM, we use a quasi-experimental approach to identify the near-miss effect of a (single) wildfire event. In particular, we use DD, an impact evaluation approach, useful for comparing changes in outcomes for an intervened and an un-intervened population, i.e., for treatment and control groups.

DD implementation involves two instances: i) the first difference, i.e., before-and-after comparison for treatment group, and ii) the second difference, i.e., before-and-after comparison for control group (Gertler, et al., 2016). In economics, the first difference or before-and-after comparison is known as the 'differences' approach (Meyer, 1995). Because we compare the treatment group with itself, it controls for time constant factors only (Gertler, et al., 2016). This is unlikely to produce valid inferences because it relies on the identifying assumption that, in the absence of the intervention, time-variant factors would be zero (Meyer, 1995). The DD approach, proposes, precisely, to introduce the second difference, which controls for time variant factors different to the intervention (Gertler, et al., 2016).

The DD approach is, however, not free from validity threats. Treatment and control groups are not assigned randomly; rather, these are assigned according to the researcher's criteria, which may lead to selection bias. Therefore, the DD approach necessitates a key identification strategy: the 'equal trends' assumption, which implies that, in absence of treatment, outcomes of treatment and control groups would have moved in tandem (Gertler, et al., 2016).

For our study, this is the assumption that, in absence of the wildfire event, sale price of near-miss and non-near-miss properties would have moved in tandem. If this assumption is not met, the estimated treatment response would be biased and lack internal validity (Meyer, 1995)[31], i.e., the estimated near-miss effect cannot be trusted to be net of all other confounding factors.

[31] Where internal validity means that "one can validly draw the inference that within the context of the study the differences in the dependent variables were caused by the differences the relevant explanatory" (Meyer, 1995, p. 152).

1.3.3 EMPIRICAL ESTIMATION OF THE NEAR-MISS EFFECT

Having described the HPM and the DD approach, we proceed to present our estimation strategy for the near-miss effect.

There are two dimensions distinguishing the structure of a quasi-experiment: the group assignment for each property (whether it is inside the near-miss area) and the timing of the potential outcome (whether it sells before or after the fire event). Parmeter and Pope (2012) provide an overview of the use of quasi-experimental methods. Our basic empirical model is as follows:

$$\begin{aligned} ln\, P_{ht} = \ & \alpha + \sum_{j=1} \beta_j Z_{hj} + \gamma Fire_{ht} + \theta Proximity_h \\ & + \varphi(Fire_{ht} \times Proximity_h) + \phi_s + \sigma_t + \mu_{ht} \end{aligned} \tag{1.1}$$

Equation **(1.1)** explains the natural logarithm of the price P of property h at time t as a function of time-invariant control variables, Z, indexed as j. In addition, we include a dummy-variable $Fire$ taking the value unity after the wildfire and whose coefficient, γ, captures the before-and-after difference in property prices, for all properties h sold after the wildfire. A further dummy-variable $Proximity$ takes the value unity for properties located in proximity to the burn scar. The coefficient θ captures the difference in property prices between proximate and non-proximate properties prior to the wildfire. Finally, we include an interaction term, $Fire_{ht} \times Proximity_h$, to measure the difference in before-and-after property prices between the treatment and control groups, or, in other words, the near-miss effect of the wildfire. Parameter φ measures this near-miss effect. The empirical model also includes suburb s and year fixed effects (FE). These are represented by ϕ_s and σ_t, respectively. Finally, we include an error term μ_{ht}. Kuminoff et al. (2010) recommend the use of a "combination of spatial fixed effects, quasi-experimental identification strategies, and temporal controls for housing market adjustment" (p. 145).

Equation **(1.2)** below extends this model by including the dummy variable $Warning$ that takes the value of unity for properties located in areas that received a warning during the wildfire. This variable is also interacted with the dummy variable, $Fire$, where the coefficient φ_2 on the interaction term represents the treatment effect associated with the warning (whilst simultaneously controlling for the effect of proximity):

$$\ln P_{ht} = \alpha + \sum_{j=1} \beta_j Z_{hj} + \gamma Fire_{ht} + \theta_1 Proximity_h + \theta_2 Warning_h + \varphi_1 (Fire_{ht} \times Proximity_h) + \varphi_2 (Fire_{ht} \times Warning_h) + \phi_s + \sigma_t + \mu_{ht} \tag{1.2}$$

In what follows, we present the centrepiece of our study, i.e., the Waroona Fire of 2016, and then we move on investigate different definitions of proximity as well as different gradations of warning.

1.4 THE WAROONA FIRE OF 2016

Two wildfires, officially known as Perth Hills (PH) 68 and PH 69, occurred during the 2015/16 bushfire season. Caused by a lightning strike at the Lane Pool Reserve, south of the Dwellingup State Forest, these originated after dark on the 5th of January 2016. The Bush Fire Brigade promptly dealt with fire PH 69. PH 68 however, went on to become what is commonly referred to as the Waroona Fire. When this fire crossed the Murray River, it became uncontrollable. The results were devastating for the communities of Waroona, Yarloop, Preston Beach and surrounding areas: 69,165 ha were burnt resulting in 181 dwellings were destroyed, and 3,300 ha of forest plantations were lost. The town of Yarloop was the most severely affected with 166 dwellings destroyed and two fatalities[32] (Government of Western Australia, 2016).

One much discussed aspect of the Waroona Fire is that, prior to its occurrence, the Department of Parks and Wildlife (DPAW) had failed to meet its hazard reduction burning (HRB) targets almost every year during the previous 12 years. In fact, due to the forest protection movement, HRB has consistently declined since the 1990s and, perhaps as a consequence, wildfires have become more frequent since the 2000s (Government of Western Australia, 2016). Several other factors also contributed to the spread of the Waroona Fire: the difficulty in accessing the fire area due to steep and rocky terrain, the very dry fuel, the sheer intensity of the fire and the presence of bauxite mining and rehabilitated forest areas that constrained fire control strategies (Government of Western Australia, 2016).

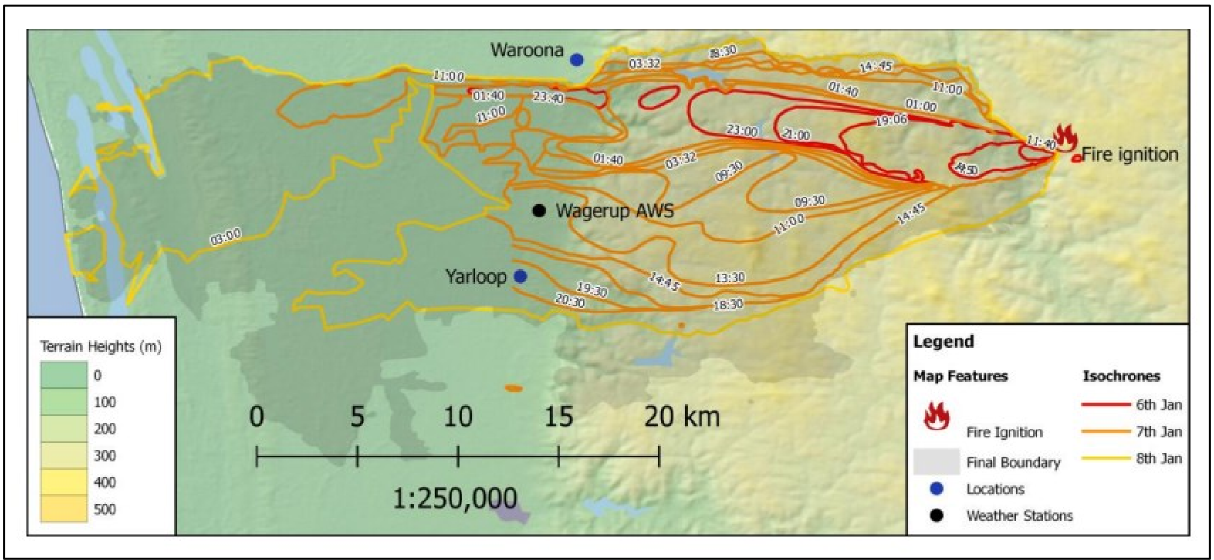
The neighbouring town of Yarloop was particularly vulnerable to the wildfire due to the number of timber properties resulting in multiple ignitions in a short period of time (Government of Western Australia, 2016). Yarloop's destruction can also be traced to poor fuel management (e.g., trees overhanging roads, long grass in some areas and forests unburned for up to 37 years), and strong evening downslope winds that spread burning embers (Government of Western Australia, 2016).

Such evening downslope winds are known as 'katabatic' winds, and these played an important role in the spread of the fire. According to Peace et al. (2017), during the first

[32] No other town experienced fatalities (Government of Western Australia, 2016).

two days of the fire the wind was blowing from east to west burning through heavy fuels, and from a terrain of 500 m height, where the fire ignited, to a terrain of 0 m height (the coastline). Moreover, the authors indicate that during the morning of the 7th of January of 2016, the winds were blowing in a south-southwesterly direction – see **Figure 1.1** below. The path of the spread of the fire played a significant role in determining near-miss areas: households located to the east of the fire ignition point were at no significant risk because the fire spread entirely to the west. Indeed, no town to the east of the fire ignition point received warnings during the first two days of the fire (Government of Western Australia 2016).

Figure 1.1: Reconstruction of the spread of the Waroona Fire



Source: Peace, et al. (2017)

1.5 DATA

To study the Waroona Fire, we use GIS open access data provided by the Department of Biodiversity, Conservation, and Attractions (DBCA). In particular, we use the *DBCA Fire History (DBCA-060)* dataset published in shapefile format in the dataWA website[33]. The shapefile contains information on the burnt area for all fires recorded in WA since 1922 and distinguishes different types of fires (wildfires, prescribed burns, plantation fires, and mining rehabilitation fires). Since our interest lies in the Waroona Fire, we filtered records of wildfires from 2016 with fire number 68 to identify the edge of the burn scar.

Australian Property Monitors (APM) provided property market data, of which we keep residential properties only. Apart from the sale price and date, these data also include a range of property characteristics, which we include in the regression. The dataset also includes properties' latitudes and longitudes, and these are used to obtain the Euclidean distance between each property and several neighbourhood, environmental and risk-moderating characteristics. For neighbourhood and environmental characteristics, we include distance to the nearest public beach and forested area, as well as to bus and rail public stops, schools, central Perth and urban land. Public beaches in WA were first identified by their name from the Surf Life Saving Western Australia website (https://www.mybeach.com.au/my-beach/). Then, we looked for latitude and longitude of each beach using Google Earth Pro. For risk moderating attributes we include distance to DFES stations with the capability to respond during a wildfire emergency and distance to the nearest sandy coastline to account for emergency evacuation sites.

Proximity treatment and control groups are defined according to the Euclidean distance between each property and the nearest edge of the final boundary of the Waroona Fire burn scar. Given that the literature does not suggest a clear cut-off

[33] This is an online data catalogue provided by the Government of Western Australia in https://catalogue.data.wa.gov.au.

distance to define an area as being in close proximity to the fire area, we are flexible when defining the proximity treatment. More precisely, we use 4 definitions of proximity: a Euclidean distance of 0-2, 0-5, 0-10, and 0-20 km from the boundary of the burn scar. Thus, the dummy variable *Proximity* takes the value of unity if the Euclidean distance between the property and the nearest edge of the burn scar is within 2, 5, 10, or 20 km. We estimate equations **(1)** and **(2)** under each of these four definitions to gain insights on the appropriate cut-off for a proximity effect. Because we are interested in the information effect and not in the direct-hit effect, we exclude all observations within the burn scar (at a 0 km distance).

We are also flexible in our definition of warnings and investigate warnings of different gradations: emergency warning alerts, recommended evacuation alerts, and directed evacuation alerts issued during the first two days of the Waroona Fire. Spatial data on these warnings are taken from the Report of the Special Inquiry on the January 2016 Waroona Fire (Government of Western Australia, 2016, pp. 159-192). Using this report, we identify towns expressly mentioned in emergency warning alerts. We also use the report to identify those areas enclosed by roads mentioned in the emergency warnings alerts. Then, we used a road network dataset provided by Geofabrik to identify those properties enclosed by the aforementioned roads. Towns that were issued evacuation alerts, either recommended or directed, are also identified from this report. Recommended evacuation alerts are issued by the Controlling Agency (DFES or DPAW) when the risk is not perceived as imminent and advice the community to evacuate but does not require to do so. If the risk is perceived as imminent and life-threatening, a directed evacuation alert is issued (Government of Western Australia, 2016, p. 185). To precisely identify the properties within the towns of interest, we use the latitudes and longitudes of properties provided by APM and a shapefile with the town boundaries provided by the Government of Western Australia (i.e., the *Localities (LGATE-234)* dataset obtained from dataWA). Because we are interested in the near-miss effect as an information effect, our main results consider emergency warning alerts only. Nevertheless, we estimate equation **(2)** using evacuation alerts as the highest gradation of warning and present these as additional results.

Figure 1.2 provides a visual representation of treatment and control groups for our main results. For the proximity treatment of 0-2 km, all properties within the 0-2 km distance band are treated properties and the rest are observations in the control group[34]. The same logic applies for the 0-5, 0-10 and 0-20 km distance bands. For the warning treatment, we present two models: A and B. Model A includes as treated properties those that fall within the boundaries of towns expressly mentioned in the emergency warning alerts. For Model B, we expand the treatment group by also including those properties in areas partially or totally enclosed by roads named in warnings. **Table 1.5.1** below shows two examples of emergency warning alerts. Examples #1 and #2 would apply for Model B, whereas only example #2 would apply for Model A.

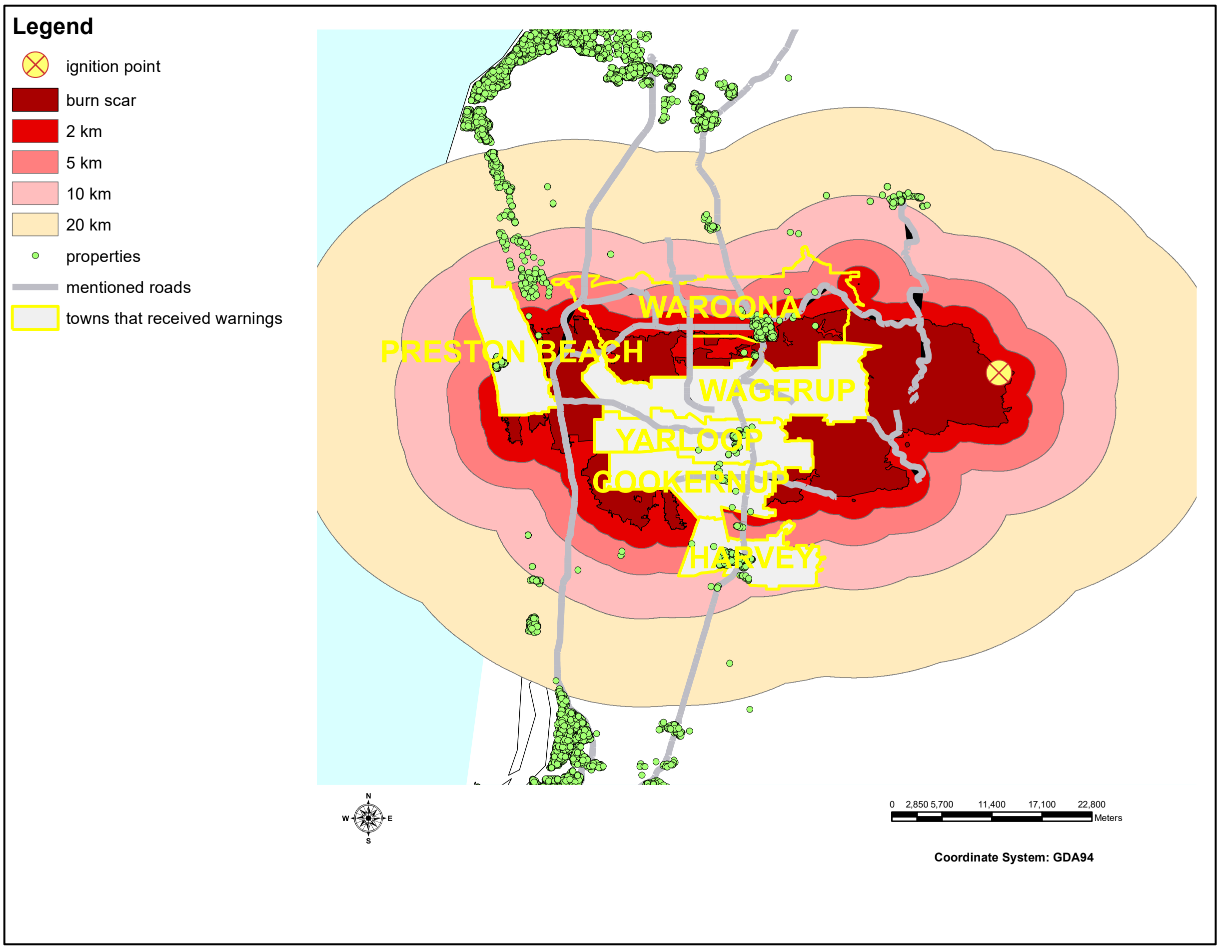
Table 1.5.1: Examples of emergency warning alerts

#	Date and time of issue	Issued for
1	06 January 2016, 22:25	*"...people bounded by Willowdale Road, Johnston Road, Somers Road, Coronation Road and Nanga Brook Road including Waroona townsite in the Shire of Waroona."*
2	07 January 2016, 19:35	*"... people in the Harvey townsite and surrounding areas in the Shire of Harvey. This includes the towns of Wagerup, Yarloop and Cookernup."*

Source: own elaboration. Based on Government of Western Australia (2016)

[34] Given that the map is a close-up of the fire area, not all observations in the control group can be visualized.

Figure 1.2: Map of treated properties



Source: Own elaboration. Based on Australian Government Data, Government of Western Australia, and Australian Property Monitors data

The final dataset includes 51,055 observations, all of which are properties sold within 203 suburbs of the Peel and Southwest regions of WA during 2010-2019. **Table 1.5.2** below shows the number of observations sold before and after the Waroona Fire for the treatment and control groups, and for the proximity and warning treatments, respectively.

Table 1.5.2: Number of observations for treatment and control groups

	Before		After	
	Treatment	Control	Treatment	Control
Treatment 1: Proximity (km)				
0 - 2	371	32,411	191	18,082
0 - 5	454	32,328	229	18,044
0 - 10	716	32,066	393	17,880
0 - 20	1,170	31,612	655	17,618
Treatment 2: Emergency warning alerts				
Model A	629	32,153	312	17,961
Model B	666	32,116	333	17,940

Our estimation equations include suburb fixed effects and year fixed effects. Suburb fixed effects enable us to control for differences in climate, crime incidence, local government management, and mean income levels, as well as for differences in the implicit prices of property characteristics caused by market segmentation. Annual time dummies control for autonomous trends in property prices[35]. For detailed information on data sources and summary statistics, see **Appendix C: Data**.

1.6 RESULTS

Our main results for estimated treatment effects are shown in **Table 1.6.1** below. Model 1 includes only proximity to identify near-miss properties. However, whilst proximity has, as noted, been widely used to identify near-miss properties, in this instance there is no statistically significant price change for properties in any distance band. Nevertheless, when we include warnings as an additional treatment this result changes. More specifically, when warnings are included, we find a positive near-miss effect from proximity, significant at the five percent level, irrespective of how the

[35] Suburb fixed effects are dummies that take the value of unity if the property is located within the suburb, as indicated by APM property market data. Year fixed effects are time dummies that take the value of unity if the property was sold during the calendar year, also indicated by APM property market data.

warning treatment group is defined, at least for the 0-2 and 0-5 km distance bands. On the other hand, we find a near-miss effect from the warning treatment that is both negative and significant at the 10 percent level if, and only if, the warnings mentioned named locations (Model 2A) rather than enclosed areas (Model 2B).

Table 1.6.1: Main Results

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Model 1				
Fire x Proximity ($\hat{\varphi}$)	0.0365	0.0284	-0.00633	0.00158
	(0.0260)	(0.0237)	(0.0184)	(0.0144)
Model 2A				
Fire x Proximity ($\hat{\varphi}_1$)	0.0941**	0.0804**	-0.0354	0.00219
	(0.0409)	(0.0391)	(0.0448)	(0.0201)
Fire x Warning ($\hat{\varphi}_2$)	-0.0579*	-0.0559*	0.0342	-0.00282
	(0.0319)	(0.0335)	(0.0491)	(0.0283)
Model 2B				
Fire x Proximity ($\hat{\varphi}_1$)	0.0824**	0.0815**	-0.0619	0.000860
	(0.0393)	(0.0405)	(0.0555)	(0.0208)
Fire x Warning ($\hat{\varphi}_2$)	-0.0464	-0.0544	0.0622	-0.000057
	(0.0297)	(0.0336)	(0.0588)	(0.0284)
For all Models:				
Observations	51,055	51,055	51,055	51,055
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
R^2 is 0.614.

It is interesting that, when we model the near-miss effect as a multi-dimensional effect that depends on proximity to the burn scar and emergency warning alerts, we get near-miss effects that move in opposite directions. On one hand, properties located 0-2 and 0-5 km from the burn scar experienced, on average, a price mark-up of 9.41% and 8.04%, respectively, after the Waroona Fire, compared to properties located beyond 0-2 and 0-5 km from the burn scar, respectively. On the other hand, properties in locations expressly mentioned in the emergency warning alerts, experienced a price discount of 5.79% and 5.59% (depending on the definition of the proximity distance band) after the Waroona Fire, compared to properties in locations not expressly named in the emergency warning alerts.

Nevertheless, the warning treatment effect fades away when the warning group dummy takes the value of unity for all properties in locations that were either expressly named in the warnings or enclosed by mentioned roads. In spite of this, the estimated proximity treatment effect remains positive and statistically significant at the five percent level, suggesting a price mark-up of 8.24% and 8.15% respectively, for properties located within 0-2 and 0-5 km from the burn scar.

Models 1, 2A and 2B include a full set of control variables, as well as suburb and year FE. Although they are not the focus of attention, the coefficients for control variables generally display the expected sign and are statistically significant. For example, we find that properties with more bathrooms and bedrooms, and a swimming pool all command a significantly higher price. Interestingly, the value of a property increases with distance to a forested area. We think this might be due to the heightened risk of fire outweighing any amenity benefit. Similarly, properties closer to any type of DFES fire station (with the capability to respond during a fire emergency) are more expensive. The complete regression outputs for our main results can be found in **Appendix A: Main Results**.

1.7 DISCUSSION

The DD identification technique assumes that, in absence of treatment, the outcomes of treatment and control groups would have moved in tandem (Gertler, et al., 2016). For our purposes this means that, in absence of the fire event, the sale price of near-miss and non near-miss properties would have moved in tandem. However, if the trend in sale prices for the control group were to differ from that of the treatment group, the implementation of the DD approach would yield a biased estimate of the treatment response. The possible violation of the so-called 'parallel trends' assumption therefore represents the main threat to the validity of our results.

Because the counterfactual is unobservable, it is not possible to directly test the parallel trends assumption. However, its plausibility is customarily gauged by comparing outcomes for the treatment and control groups in the pre-treatment period, i.e., comparing property prices across the near-miss and non near-miss groups prior to the Waroona Fire.

Fortunately, our data does not call into question the parallel trends assumption for the log of sale price. **Figure 1.3**, **Figure 1.4**, and **Figure 1.5**, display the log of sale price, 2010-2019, for our treatment and control groups. The treatment group is proximity to the burn scar of 0-2 and 0-5 km for **Figure 1.3** and **Figure 1.4**, whereas the treatment group is being in a location expressly named in emergency warning alerts for **Figure 1.5**. In all cases, the price trends appear parallel before the Waroona Fire (and as expected there is a clear change in trends from 2016 onwards).

Figure 1.3: parallel trends check, 2 km proximity treatment

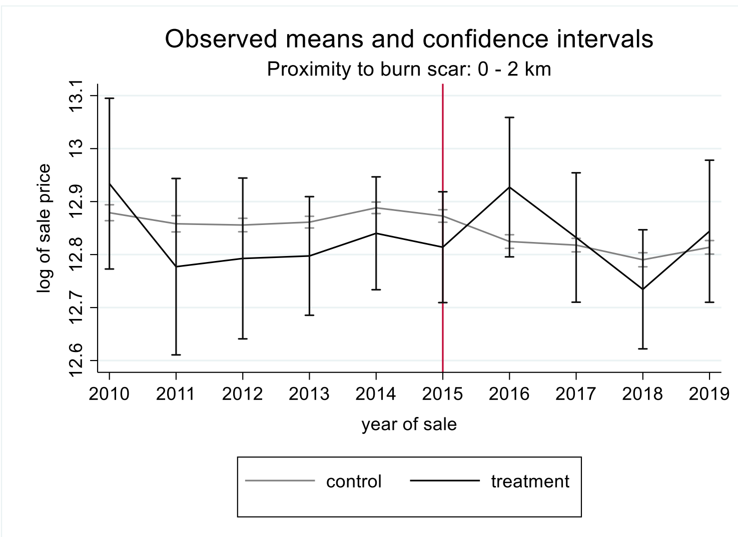


Figure 1.4: parallel trends check, 5 km proximity treatment

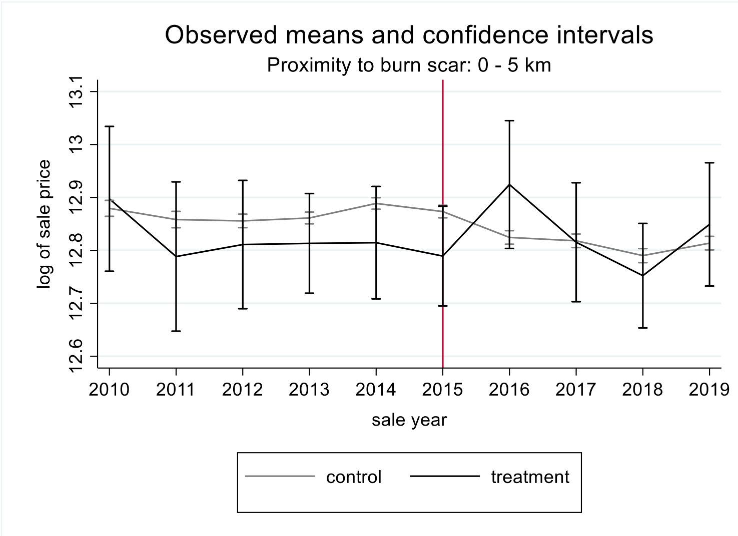
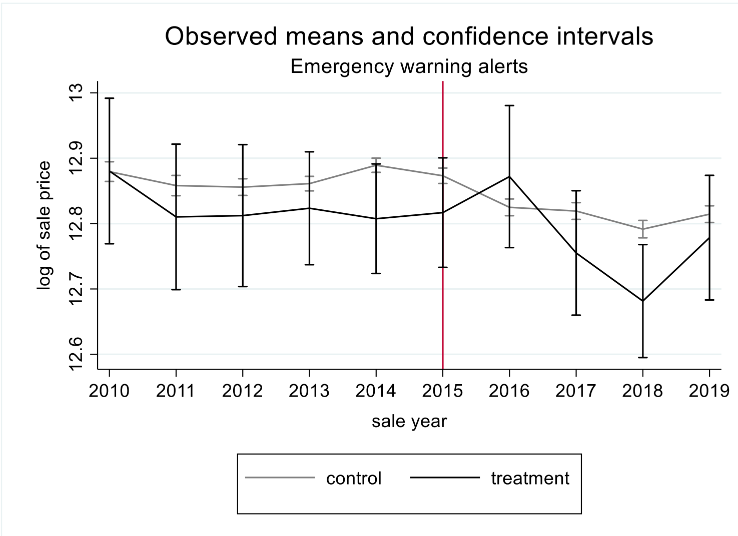


Figure 1.5: parallel trends check, emergency warning



As a further check on the credibility of our main findings, we undertake a placebo test involving the date of the wildfire. This test involves substituting the dummy variable $Fire$ with a dummy variable $Placebo$, which takes the value of unity for properties sold on or after 1st of January of 2014 (as opposed to the actual date of the wildfire: 6th of January 2016). The estimates of the treatment effects are all statistically insignificant, even at the 10 percent level, exactly as they should be (see **Table 1.7.1** below).

Table 1.7.1: Placebo test

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Equation 1.1				
Placebo x Proximity	0.0259	0.0227	-0.00128	-0.00561
	(0.0251)	(0.0226)	(0.0180)	(0.0141)
Equation 1.2, Model A				
Placebo x Proximity	0.0560	0.0548	-0.0282	-0.0156
	(0.0386)	(0.0371)	(0.0481)	(0.0202)
Placebo x Warning	-0.0304	-0.0343	0.0308	0.0183
	(0.0298)	(0.0318)	(0.0518)	(0.0278)
Equation 1.2, Model B				
Placebo x Proximity	0.0494	0.0552	-0.0605	-0.0184
	(0.0375)	(0.0388)	(0.0634)	(0.0209)
Placebo x Warning	-0.0237	-0.0331	0.0642	0.0222
	(0.0281)	(0.0322)	(0.0660)	(0.0279)

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

Next, we present additional results where we consider different gradations of warning. We examine two models: Models 2C and 2D. Model 2C examines the warning treatment effect triggered by directed evacuation alerts. As shown in **Table 1.7.2** below, both the warning and proximity treatment effects are statistically insignificant. Model 2D, on the other hand, expands the warning treatment group such that it also includes properties within towns that received recommended evacuation alerts, i.e., the warning treatment effect is that triggered by both directed and recommended evacuation alerts. For this model, the warning and proximity treatment effects hold the expected signs and are both statistically significant at the 5 percent level. In particular, we find that properties within 0-2 and 0-5 km from the burn scar experience a price mark-up of 5.2 and 5.7 percent, respectively, after the Waroona Fire. After accounting for a 0-2 and 0-5 km proximity effect, we find that properties that received evacuation alerts of any sort experienced a price discount of 6.0 and 6.5 percent, respectively. Nevertheless, when we account for 0-10 and 0-20 km proximity effects, the proximity treatment effect is no longer significant, and the corresponding warning treatment effects remain at the expected magnitude but at a lower significance.

Table 1.7.2: Additional Results

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Model 2C				
Fire x Warning ($\hat{\varphi}_2$)	-0.0121	0.00122	0.0452	0.0347
	(0.0573)	(0.0554)	(0.0522)	(0.0505)
Fire x Proximity ($\hat{\varphi}_1$)	0.0468	0.0335	-0.0110	-0.000341
	(0.0310)	(0.0272)	(0.0199)	(0.0150)
Model 2D				
Fire x Warning ($\hat{\varphi}_2$)	-0.0604**	-0.0646**	-0.0663*	-0.0596*
	(0.0283)	(0.0291)	(0.0365)	(0.0316)
Fire x Proximity ($\hat{\varphi}_1$)	0.0566**	0.0516**	0.0242	0.0180
	(0.0273)	(0.0255)	(0.0249)	(0.0168)
For both models:				
Observations	51,055	51,055	51,055	51,055
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

In relation to these results, we believe that Model 2C is not statistically significant because the treatment group is too small. Only the towns of Preston Breach and Yarloop received directed evacuation alerts, amounting to only 145 observations in the treatment group (81 before the Waroona Fire and 64 after). On the other hand, the towns of Preston Beach, Yarloop, and Harvey received evacuation alerts of any sort (recommended and directed), amounting to 509 observations (327 before the Waroona Fire and 182 after). Additionally, given that the towns of Preston Beach, Yarloop, and Harvey also received emergency warning alerts, we interpret the higher significance of the warning treatment effect in Model D as the stronger capacity of evacuations to trigger vulnerability feelings. Indeed, evacuation alerts explicitly call for action, whilst emergency warning alerts do so implicitly.

We also investigated a model that contained all different types of warning together at the same time (results not shown). The findings from this model continue to display a negative effect from recommended evacuation that is depending on the distance band statistically significant at the one percent level.

The key message contained in this study is that including spatial information on warnings makes a significant difference when it comes to identifying the near-miss effect of wildfire events. More specifically, we argue that the near-miss effect should be broken down into two components: a proximity treatment effect and a warning treatment effect. Otherwise, given that they overlap, the negative effect from the warning treatment obscures the positive effect from the proximity treatment.

In the case of an event as large as the Waroona Fire, the near-miss experience is heterogeneous across the areas surrounding the burn scar, i.e., only some locations within 0-2 or 0-5 km from the burn scar received warnings (e.g., because they were in the path of the approaching fire, moving from the ignition point from the east to the west-southwest). Essentially, we refine the estimation of the near-miss effect by recognizing that near-miss areas are not limited to areas in proximity to the burn scar but also include areas where households received some type of warning that increased the saliency of the event. Our approach therefore investigates the near-miss effect differentiated by distinct near-miss experiences. On one hand, we argue that the proximity treatment effect reflects an 'impure' near-miss effect that arises from a change in amenity levels combined with a change in risk perception. On the other hand, we argue that – after controlling for proximity to the burn scar - the warning treatment effect reflects a 'pure' near-miss effect that arises from a change in risk perception.

We interpret our main findings as follows. We believe that the pure near-miss effect associated with warnings triggers longer-term feelings of vulnerability, manifesting in a property price discount. The price markup associated with the proximity to the burn scar is, however, the result of an impure information effect: a positive effect from a reduction in future risk and a negative disamenity effect. Bluntly, the fire event consumes fuel that reduces the probability of a future fire. Plausibly, the burnt landscape and associated loss of biodiversity results in a disamenity impact. Nevertheless, our results suggest that the risk-reduction effect dominates over any disamenity impact. Hansen and Naughton (2013) have suggested that a wildfire might even improve the view or increase the scope for recreational activities. Whilst this would reinforce the risk-reduction effect we regard the possibility as somewhat far-fetched. In addition, it is possible that buyers and sellers perceived the Waroona Fire as a resilient near-miss event, precisely because the property escaped harm, and even more so if no warnings were issued for the town it belongs to. Regardless of *what exactly* causes property prices to increase with proximity to the burn scar of the Waroona Fire, we will, in **CHAPTER 3**, confirm this result, i.e., that property prices are generally higher when in close proximity to a burn scar, and that this is most likely explained by a risk reduction effect.

Moreover, we believe that the different estimation results for the warning treatment effect between Model 2A and 2B is explained by the clarity of the communications. In particular, we believe that emergency warning alerts that expressly mentioned the towns at risk are clearer than those that refer to areas enclosed by roads. And this is supported by the Report of the Special Inquiry on the January 2016 Waroona Fire (Government of Western Australia, 2016, p. 186). This finding aligns with Dillon &

Tinsley (2016)'s study, which proposes that risk communication that highlights vulnerability may alter perceived probabilities of risk upwards.

It is interesting to note that when we exclude warnings, with the exception of Hansen and Naughton (2013), our findings still differ to those contained in literature on near-miss wildfire events. The literature suggests a statistically significant negative near-miss effect from proximity to the burn scar whereas we find no effect significant even at the 10 percent level. However, with the exception of Loomis (2004), the literature deals with repeated and (in contrast to Waroona) small, fire events.

It appears that DFES decisions made during the wildfire had a significant impact on the wealth of households. More specifically, after controlling for proximity treatments of 0-2 and 0-5 km from the burn scar, the warning treatment cost households 23,685 and 22,867 Australian dollars (AUD), respectively – see **Table 1.7.3** below.

Table 1.7.3: Average treatment effects for Model 2A

Treatment Group	Mean price (AUD)	Treatment effect (%)	Treatment effect (AUD)
0-2 km	420,132	9.41	+ 39,534
0-5 km	415,370	8.04	+ 33,396
Towns expressly mentioned in the emergency warning alerts	409,069	[-5.79, -5.59]	[-23,685, -22,867]

1.8 CONCLUSION

Current hedonic analyses of the near-miss phenomenon for wildfire events exhibit certain shortcomings. In some, there is no explicit identification strategy and no measure of the distance to the burn scar. More importantly, the literature fails to address the multidimensional nature of the near-miss effect. Our study recognises that not all properties in proximity to the burn scar have the same near-miss experience:

some receive explicit warnings. This is certainly the case for warnings issued by the DFES during the Waroona Fire.

We contribute to the literature by combining these two types of information: information on proximity to the burn scar and on locations that received warnings. We find that including both sorts of information makes a significant difference when estimating the near-miss effect. We argue that the warning treatment effect arises from an increased risk perception triggered by vulnerability feelings. We argue that the proximity treatment effect entangles two opposing impacts: a positive impact from a diminished future risk and a negative disamenity impact. Since the proximity treatment effect is positive, our results suggest that the former dominates over the latter. The need to disentangle the different components of the proximity treatment effect remains a challenge. Clearly, it will be interesting to discover what impact HRB has on property prices.

Climate change and population growth in fire-prone areas present an urgent challenge. Policymakers need to understand better whether wildfires serve as a wake-up call highlighting households' vulnerability or simply reinforce feelings of resiliency among households in near-miss areas. Our findings suggest that warnings reinforce feelings of vulnerability. Because of the impact on property prices, authorities should however be careful not to issue blanket warnings. Furthermore, we find that warnings update risk perception most effectively when clearly communicated.

1.9 APPENDIX

APPENDIX A: MAIN RESULTS

Table 1.9.1: Estimations Results for Model 1

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Fire	-0.0667*	-0.0672*	-0.0663	-0.0665*
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
Proximity	-0.0163	-0.0132	-0.00522	-0.00140
	(0.0160)	(0.0145)	(0.0115)	(0.00966)
Fire#Proximity	0.0365	0.0284	-0.00633	0.00158
	(0.0260)	(0.0237)	(0.0184)	(0.0144)
AreaSize	8.45e-07***	8.45e-07***	8.45e-07***	8.45e-07***
	(6.13e-08)	(6.13e-08)	(6.13e-08)	(6.13e-08)
Baths	0.155***	0.155***	0.155***	0.155***
	(0.00311)	(0.00311)	(0.00311)	(0.00311)
Bedrooms	0.0656***	0.0656***	0.0657***	0.0657***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
HasStudy	0.0921***	0.0921***	0.0921***	0.0921***
	(0.00314)	(0.00314)	(0.00314)	(0.00314)
HasSeparateDining	0.000248	0.000281	0.000250	0.000256
	(0.00568)	(0.00568)	(0.00568)	(0.00568)
HasFamilyRoom	0.0465***	0.0465***	0.0465***	0.0465***
	(0.00321)	(0.00321)	(0.00321)	(0.00321)
HasSunroom	-0.00165	-0.00165	-0.00180	-0.00171
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
HasRumpusRoom	0.00888*	0.00888*	0.00884*	0.00885*
	(0.00455)	(0.00455)	(0.00455)	(0.00455)
HasFireplace	0.0151***	0.0151***	0.0151***	0.0151***
	(0.00498)	(0.00498)	(0.00498)	(0.00498)
HasWalkInWardrobe	0.00719*	0.00718*	0.00715*	0.00716*
	(0.00426)	(0.00426)	(0.00426)	(0.00426)
HasCourtyard	-0.00507	-0.00508	-0.00504	-0.00505
	(0.00600)	(0.00600)	(0.00600)	(0.00600)
HasInternalLaundry	0.0279***	0.0279***	0.0278***	0.0279***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
HasHeating	0.00984**	0.00985**	0.00982**	0.00984**
	(0.00496)	(0.00496)	(0.00496)	(0.00496)
HasAirConditioning	-0.00674**	-0.00675**	-0.00677**	-0.00677**
	(0.00289)	(0.00289)	(0.00289)	(0.00289)
HasBalcony	0.153***	0.153***	0.153***	0.153***
	(0.00520)	(0.00520)	(0.00520)	(0.00520)
HasBarbeque	0.0187***	0.0188***	0.0187***	0.0187***
	(0.00598)	(0.00598)	(0.00598)	(0.00598)
HasPolishedTimberFloor	0.0347***	0.0347***	0.0348***	0.0347***
	(0.00627)	(0.00627)	(0.00627)	(0.00627)
HasEnsuite	0.0176***	0.0176***	0.0177***	0.0177***

Table 1.9.1: Estimations Results for Model 1

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.00363)	(0.00363)	(0.00363)	(0.00363)
HasSpa	0.0541***	0.0541***	0.0541***	0.0541***
	(0.00566)	(0.00566)	(0.00566)	(0.00566)
HasGarage	0.0945***	0.0945***	0.0945***	0.0945***
	(0.00292)	(0.00292)	(0.00292)	(0.00292)
HasLockUpGarage	-0.0238***	-0.0238***	-0.0238***	-0.0238***
	(0.00565)	(0.00565)	(0.00565)	(0.00565)
HasPool	0.108***	0.108***	0.108***	0.108***
	(0.00456)	(0.00456)	(0.00456)	(0.00456)
HasTennisCourt	0.0725**	0.0725**	0.0726**	0.0725**
	(0.0339)	(0.0339)	(0.0339)	(0.0339)
HasAlarm	0.0879***	0.0879***	0.0879***	0.0879***
	(0.00626)	(0.00626)	(0.00626)	(0.00626)
Apartment House	0.468***	0.468***	0.468***	0.468***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Cottage	-0.259***	-0.259***	-0.259***	-0.259***
	(0.0658)	(0.0658)	(0.0658)	(0.0658)
Duplex	-0.0954***	-0.0954***	-0.0953***	-0.0953***
	(0.00839)	(0.00839)	(0.00839)	(0.00839)
Flat	-0.332***	-0.332***	-0.332***	-0.332***
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Patio House	-0.160**	-0.160**	-0.160**	-0.160**
	(0.0750)	(0.0750)	(0.0750)	(0.0750)
Quadruplex	0.0187	0.0187	0.0188	0.0189
	(0.129)	(0.129)	(0.129)	(0.129)
Semi	-0.0128	-0.0127	-0.0128	-0.0128
	(0.102)	(0.102)	(0.102)	(0.102)
Terrace	0.0130	0.0130	0.0128	0.0130
	(0.0834)	(0.0834)	(0.0834)	(0.0834)
Townhouse	-0.0747***	-0.0746***	-0.0747***	-0.0746***
	(0.00702)	(0.00702)	(0.00702)	(0.00702)
Triplex	0.370***	0.370***	0.370***	0.370***
	(0.110)	(0.110)	(0.110)	(0.110)
Unit	-0.130***	-0.130***	-0.130***	-0.130***
	(0.00633)	(0.00633)	(0.00633)	(0.00633)
Villa	-0.369***	-0.369***	-0.370***	-0.369***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)
Villa House	-0.176***	-0.176***	-0.177***	-0.177***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)
nd_bus_standard	-1.09e-07	-1.09e-07	-1.01e-07	-1.07e-07
	(1.65e-07)	(1.65e-07)	(1.65e-07)	(1.66e-07)
nd_bus_cat	-4.27e-07	-4.11e-07	-2.58e-07	-4.29e-07
	(1.72e-06)	(1.72e-06)	(1.73e-06)	(1.74e-06)
nd_rail	-1.17e-07	-1.21e-07	-1.64e-07	-1.10e-07
	(4.19e-07)	(4.21e-07)	(4.25e-07)	(4.26e-07)
nd_cas	2.01e-07	2.14e-07	3.43e-07	2.35e-07
	(6.13e-07)	(6.16e-07)	(6.15e-07)	(6.74e-07)
nd_perth	5.03e-07	4.92e-07	3.79e-07	5.00e-07

Table 1.9.1: Estimations Results for Model 1

	(1)	(2)	(3)	(4)
	0-2 km	0-5 km	0-10 km	0-20 km
VARIABLES	lnPrice	lnPrice	lnPrice	lnPrice
	(1.35e-06)	(1.36e-06)	(1.37e-06)	(1.37e-06)
urban	-0.00745**	-0.00747**	-0.00746**	-0.00734**
	(0.00346)	(0.00346)	(0.00346)	(0.00346)
nd_forest	5.99e-06*	6.01e-06*	6.05e-06*	6.00e-06*
	(3.09e-06)	(3.09e-06)	(3.09e-06)	(3.09e-06)
nd_wetland	2.46e-07	2.45e-07	2.43e-07	2.38e-07
	(1.93e-07)	(1.93e-07)	(1.91e-07)	(1.92e-07)
nd_beach	1.82e-08	1.71e-08	1.66e-08	-2.94e-09
	(3.06e-07)	(3.04e-07)	(2.98e-07)	(3.01e-07)
nd_sandycoastline	-8.64e-08	-8.61e-08	-9.18e-08	-6.46e-08
	(3.22e-07)	(3.21e-07)	(3.15e-07)	(3.16e-07)
nd_fstation	-1.55e-06	-1.55e-06	-1.62e-06*	-1.52e-06
	(9.65e-07)	(9.66e-07)	(9.67e-07)	(9.63e-07)
2011	-0.0439***	-0.0439***	-0.0439***	-0.0439***
	(0.00628)	(0.00628)	(0.00628)	(0.00628)
2012	-0.0538***	-0.0538***	-0.0538***	-0.0538***
	(0.00595)	(0.00595)	(0.00595)	(0.00595)
2013	-0.0643***	-0.0643***	-0.0643***	-0.0643***
	(0.00571)	(0.00572)	(0.00571)	(0.00572)
2014	-0.0506***	-0.0506***	-0.0506***	-0.0506***
	(0.00577)	(0.00577)	(0.00577)	(0.00577)
2015	-0.0874***	-0.0874***	-0.0874***	-0.0874***
	(0.00593)	(0.00593)	(0.00593)	(0.00593)
2016	-0.0713*	-0.0708*	-0.0712*	-0.0712*
	(0.0404)	(0.0404)	(0.0404)	(0.0404)
2017	-0.114***	-0.113***	-0.114***	-0.114***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2018	-0.147***	-0.146***	-0.146***	-0.146***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2019	-0.142***	-0.142***	-0.142***	-0.142***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
Constant	12.63***	12.63***	12.63***	12.63***
	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Observations	51,055	51,055	51,055	51,055
R-squared	0.614	0.614	0.614	0.614
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table 1.9.2: Estimation Results for Model 2A

	(1)	(2)	(3)	(4)
	0-2 km	0-5 km	0-10 km	0-20 km
VARIABLES	lnPrice	lnPrice	lnPrice	lnPrice
Fire	-0.0662	-0.0670*	-0.0660	-0.0664*

Table 1.9.2: Estimation Results for Model 2A

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
Warning	0.00403	0.00313	-0.0239	-0.0144
	(0.0183)	(0.0195)	(0.0336)	(0.0179)
Fire#Warning	-0.0579*	-0.0559*	0.0342	-0.00282
	(0.0319)	(0.0335)	(0.0491)	(0.0283)
Proximity	-0.0201	-0.0160	0.0159	0.00727
	(0.0242)	(0.0233)	(0.0320)	(0.0142)
Fire#Proximity	0.0941**	0.0804**	-0.0354	0.00219
	(0.0409)	(0.0391)	(0.0448)	(0.0201)
AreaSize	8.45e-07***	8.45e-07***	8.44e-07***	8.45e-07***
	(6.13e-08)	(6.13e-08)	(6.13e-08)	(6.13e-08)
Baths	0.155***	0.155***	0.155***	0.155***
	(0.00311)	(0.00311)	(0.00311)	(0.00311)
Bedrooms	0.0656***	0.0656***	0.0657***	0.0657***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
HasStudy	0.0921***	0.0921***	0.0921***	0.0921***
	(0.00314)	(0.00314)	(0.00314)	(0.00314)
HasSeparateDining	0.000232	0.000314	0.000213	0.000254
	(0.00568)	(0.00568)	(0.00569)	(0.00568)
HasFamilyRoom	0.0465***	0.0465***	0.0465***	0.0465***
	(0.00321)	(0.00321)	(0.00321)	(0.00321)
HasSunroom	-0.00180	-0.00178	-0.00173	-0.00177
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
HasRumpusRoom	0.00884*	0.00888*	0.00882*	0.00884*
	(0.00455)	(0.00455)	(0.00456)	(0.00456)
HasFireplace	0.0151***	0.0151***	0.0151***	0.0151***
	(0.00498)	(0.00498)	(0.00498)	(0.00498)
HasWalkInWardrobe	0.00718*	0.00715*	0.00717*	0.00717*
	(0.00426)	(0.00426)	(0.00426)	(0.00426)
HasCourtyard	-0.00500	-0.00501	-0.00505	-0.00504
	(0.00600)	(0.00600)	(0.00600)	(0.00600)
HasInternalLaundry	0.0279***	0.0279***	0.0278***	0.0278***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
HasHeating	0.00983**	0.00988**	0.00981**	0.00985**
	(0.00496)	(0.00496)	(0.00496)	(0.00496)
HasAirConditioning	-0.00671**	-0.00673**	-0.00676**	-0.00676**
	(0.00289)	(0.00289)	(0.00289)	(0.00289)
HasBalcony	0.153***	0.153***	0.153***	0.153***
	(0.00520)	(0.00520)	(0.00520)	(0.00520)
HasBarbeque	0.0187***	0.0188***	0.0187***	0.0187***
	(0.00598)	(0.00598)	(0.00598)	(0.00598)
HasPolishedTimberFloor	0.0348***	0.0348***	0.0348***	0.0347***
	(0.00627)	(0.00627)	(0.00627)	(0.00627)
HasEnsuite	0.0176***	0.0177***	0.0176***	0.0177***
	(0.00363)	(0.00363)	(0.00363)	(0.00363)
HasSpa	0.0542***	0.0542***	0.0541***	0.0541***
	(0.00566)	(0.00566)	(0.00566)	(0.00566)
HasGarage	0.0945***	0.0945***	0.0945***	0.0945***

Table 1.9.2: Estimation Results for Model 2A

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.00292)	(0.00292)	(0.00292)	(0.00292)
HasLockUpGarage	-0.0239***	-0.0239***	-0.0238***	-0.0238***
	(0.00565)	(0.00565)	(0.00565)	(0.00565)
HasPool	0.108***	0.108***	0.108***	0.108***
	(0.00456)	(0.00456)	(0.00456)	(0.00456)
HasTennisCourt	0.0729**	0.0729**	0.0726**	0.0725**
	(0.0339)	(0.0339)	(0.0339)	(0.0339)
HasAlarm	0.0879***	0.0879***	0.0879***	0.0879***
	(0.00626)	(0.00626)	(0.00626)	(0.00626)
Apartment House	0.468***	0.468***	0.468***	0.468***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Cottage	-0.260***	-0.260***	-0.259***	-0.259***
	(0.0658)	(0.0658)	(0.0658)	(0.0658)
Duplex	-0.0953***	-0.0953***	-0.0953***	-0.0954***
	(0.00839)	(0.00839)	(0.00839)	(0.00839)
Flat	-0.332***	-0.332***	-0.331***	-0.331***
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Patio House	-0.160**	-0.160**	-0.160**	-0.160**
	(0.0750)	(0.0750)	(0.0750)	(0.0750)
Quadruplex	0.0188	0.0189	0.0188	0.0189
	(0.129)	(0.129)	(0.129)	(0.129)
Semi	-0.0127	-0.0126	-0.0127	-0.0127
	(0.102)	(0.102)	(0.102)	(0.102)
Terrace	0.0129	0.0129	0.0128	0.0128
	(0.0834)	(0.0834)	(0.0834)	(0.0834)
Townhouse	-0.0748***	-0.0747***	-0.0747***	-0.0747***
	(0.00702)	(0.00702)	(0.00703)	(0.00703)
Triplex	0.370***	0.370***	0.370***	0.370***
	(0.110)	(0.110)	(0.110)	(0.110)
Unit	-0.131***	-0.130***	-0.130***	-0.130***
	(0.00633)	(0.00633)	(0.00633)	(0.00633)
Villa	-0.370***	-0.370***	-0.370***	-0.369***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)
Villa House	-0.177***	-0.177***	-0.177***	-0.176***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)
nd_bus_standard	-8.60e-08	-8.92e-08	-9.92e-08	-1.12e-07
	(1.67e-07)	(1.66e-07)	(1.65e-07)	(1.66e-07)
nd_bus_cat	-1.81e-07	-2.19e-07	-2.57e-07	-4.05e-07
	(1.74e-06)	(1.73e-06)	(1.73e-06)	(1.74e-06)
nd_rail	-1.71e-07	-1.62e-07	-1.62e-07	-1.28e-07
	(4.24e-07)	(4.23e-07)	(4.25e-07)	(4.26e-07)
nd_cas	1.84e-07	1.77e-07	2.87e-07	4.58e-08
	(6.13e-07)	(6.18e-07)	(6.26e-07)	(6.99e-07)
nd_perth	3.13e-07	3.42e-07	3.77e-07	4.91e-07
	(1.37e-06)	(1.37e-06)	(1.37e-06)	(1.37e-06)
urban	-0.00732**	-0.00730**	-0.00738**	-0.00762**
	(0.00346)	(0.00347)	(0.00346)	(0.00347)
nd_forest	6.23e-06**	6.18e-06**	6.10e-06**	6.19e-06**

Table 1.9.2: Estimation Results for Model 2A

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(3.09e-06)	(3.09e-06)	(3.09e-06)	(3.09e-06)
nd_wetland	2.20e-07	2.23e-07	2.40e-07	2.58e-07
	(1.95e-07)	(1.94e-07)	(1.91e-07)	(1.93e-07)
nd_beach	-3.40e-08	-2.63e-08	1.14e-08	6.73e-08
	(3.10e-07)	(3.08e-07)	(2.98e-07)	(3.08e-07)
nd_sandycoastline	-4.26e-08	-4.87e-08	-8.62e-08	-1.46e-07
	(3.25e-07)	(3.23e-07)	(3.15e-07)	(3.25e-07)
nd_fstation	-1.61e-06*	-1.61e-06*	-1.62e-06*	-1.62e-06*
	(9.68e-07)	(9.68e-07)	(9.68e-07)	(9.68e-07)
2011	-0.0439***	-0.0439***	-0.0439***	-0.0439***
	(0.00628)	(0.00628)	(0.00628)	(0.00628)
2012	-0.0538***	-0.0538***	-0.0538***	-0.0538***
	(0.00595)	(0.00595)	(0.00595)	(0.00595)
2013	-0.0643***	-0.0643***	-0.0643***	-0.0643***
	(0.00571)	(0.00572)	(0.00572)	(0.00572)
2014	-0.0506***	-0.0506***	-0.0506***	-0.0506***
	(0.00577)	(0.00577)	(0.00577)	(0.00577)
2015	-0.0873***	-0.0874***	-0.0874***	-0.0873***
	(0.00593)	(0.00593)	(0.00593)	(0.00593)
2016	-0.0715*	-0.0707*	-0.0715*	-0.0712*
	(0.0404)	(0.0404)	(0.0404)	(0.0404)
2017	-0.114***	-0.113***	-0.114***	-0.114***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2018	-0.147***	-0.146***	-0.147***	-0.146***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2019	-0.142***	-0.141***	-0.142***	-0.142***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
Constant	12.63***	12.63***	12.63***	12.63***
	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Observations	51,055	51,055	51,055	51,055
R-squared	0.614	0.614	0.614	0.614
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table 1.9.3: Estimations Results for Model 2B

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Fire	-0.0661	-0.0669*	-0.0664*	-0.0667*
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
Warning	0.00435	0.00516	-0.0349	-0.0138
	(0.0174)	(0.0197)	(0.0425)	(0.0178)
Fire#Warning	-0.0464	-0.0544	0.0622	-5.74e-05

Table 1.9.3: Estimations Results for Model 2B

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.0297)	(0.0336)	(0.0588)	(0.0284)
Proximity	-0.0209	-0.0185	0.0273	0.00701
	(0.0233)	(0.0240)	(0.0411)	(0.0145)
Fire#Proximity	0.0824**	0.0815**	-0.0619	0.000860
	(0.0393)	(0.0405)	(0.0555)	(0.0208)
AreaSize	8.45e-07***	8.45e-07***	8.44e-07***	8.45e-07***
	(6.13e-08)	(6.13e-08)	(6.13e-08)	(6.13e-08)
Baths	0.155***	0.155***	0.155***	0.155***
	(0.00311)	(0.00311)	(0.00311)	(0.00311)
Bedrooms	0.0656***	0.0656***	0.0657***	0.0657***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
HasStudy	0.0921***	0.0921***	0.0921***	0.0921***
	(0.00314)	(0.00314)	(0.00314)	(0.00314)
HasSeparateDining	0.000217	0.000296	0.000224	0.000262
	(0.00568)	(0.00568)	(0.00569)	(0.00568)
HasFamilyRoom	0.0465***	0.0465***	0.0465***	0.0465***
	(0.00321)	(0.00321)	(0.00321)	(0.00321)
HasSunroom	-0.00172	-0.00171	-0.00176	-0.00175
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
HasRumpusRoom	0.00885*	0.00888*	0.00881*	0.00884*
	(0.00455)	(0.00455)	(0.00456)	(0.00456)
HasFireplace	0.0152***	0.0151***	0.0150***	0.0151***
	(0.00498)	(0.00498)	(0.00498)	(0.00498)
HasWalkInWardrobe	0.00718*	0.00715*	0.00719*	0.00717*
	(0.00426)	(0.00426)	(0.00426)	(0.00426)
HasCourtyard	-0.00503	-0.00504	-0.00504	-0.00505
	(0.00600)	(0.00600)	(0.00600)	(0.00600)
HasInternalLaundry	0.0279***	0.0279***	0.0278***	0.0278***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
HasHeating	0.00981**	0.00985**	0.00983**	0.00984**
	(0.00496)	(0.00496)	(0.00496)	(0.00496)
HasAirConditioning	-0.00671**	-0.00673**	-0.00676**	-0.00676**
	(0.00289)	(0.00289)	(0.00289)	(0.00289)
HasBalcony	0.153***	0.153***	0.153***	0.153***
	(0.00520)	(0.00520)	(0.00520)	(0.00520)
HasBarbeque	0.0187***	0.0187***	0.0188***	0.0187***
	(0.00598)	(0.00598)	(0.00598)	(0.00598)
HasPolishedTimberFloor	0.0348***	0.0348***	0.0347***	0.0347***
	(0.00627)	(0.00627)	(0.00627)	(0.00627)
HasEnsuite	0.0176***	0.0176***	0.0176***	0.0177***
	(0.00363)	(0.00363)	(0.00363)	(0.00363)
HasSpa	0.0542***	0.0542***	0.0541***	0.0541***
	(0.00566)	(0.00566)	(0.00566)	(0.00566)
HasGarage	0.0945***	0.0945***	0.0945***	0.0945***
	(0.00292)	(0.00292)	(0.00292)	(0.00292)
HasLockUpGarage	-0.0239***	-0.0239***	-0.0238***	-0.0238***
	(0.00565)	(0.00565)	(0.00565)	(0.00565)
HasPool	0.108***	0.108***	0.108***	0.108***

Table 1.9.3: Estimations Results for Model 2B

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.00456)	(0.00456)	(0.00456)	(0.00456)
HasTennisCourt	0.0728**	0.0729**	0.0726**	0.0725**
	(0.0339)	(0.0339)	(0.0339)	(0.0339)
HasAlarm	0.0879***	0.0879***	0.0878***	0.0879***
	(0.00626)	(0.00626)	(0.00626)	(0.00626)
Apartment House	0.468***	0.468***	0.468***	0.468***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Cottage	-0.260***	-0.260***	-0.259***	-0.259***
	(0.0658)	(0.0658)	(0.0658)	(0.0658)
Duplex	-0.0953***	-0.0953***	-0.0953***	-0.0954***
	(0.00839)	(0.00839)	(0.00839)	(0.00839)
Flat	-0.332***	-0.332***	-0.331***	-0.331***
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Patio House	-0.160**	-0.160**	-0.160**	-0.160**
	(0.0750)	(0.0750)	(0.0750)	(0.0750)
Quadruplex	0.0188	0.0189	0.0188	0.0189
	(0.129)	(0.129)	(0.129)	(0.129)
Semi	-0.0127	-0.0127	-0.0128	-0.0128
	(0.102)	(0.102)	(0.102)	(0.102)
Terrace	0.0129	0.0129	0.0128	0.0128
	(0.0834)	(0.0834)	(0.0834)	(0.0834)
Townhouse	-0.0748***	-0.0747***	-0.0746***	-0.0747***
	(0.00703)	(0.00702)	(0.00703)	(0.00703)
Triplex	0.370***	0.370***	0.370***	0.370***
	(0.110)	(0.110)	(0.110)	(0.110)
Unit	-0.131***	-0.130***	-0.130***	-0.130***
	(0.00633)	(0.00633)	(0.00633)	(0.00633)
Villa	-0.370***	-0.370***	-0.370***	-0.370***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)
Villa House	-0.177***	-0.177***	-0.176***	-0.176***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)
nd_bus_standard	-9.43e-08	-9.41e-08	-1.01e-07	-1.13e-07
	(1.67e-07)	(1.66e-07)	(1.65e-07)	(1.66e-07)
nd_bus_cat	-2.31e-07	-2.36e-07	-2.60e-07	-4.00e-07
	(1.74e-06)	(1.73e-06)	(1.73e-06)	(1.74e-06)
nd_rail	-1.65e-07	-1.63e-07	-1.63e-07	-1.31e-07
	(4.24e-07)	(4.24e-07)	(4.25e-07)	(4.27e-07)
nd_cas	2.44e-07	2.35e-07	3.29e-07	1.11e-07
	(6.14e-07)	(6.16e-07)	(6.16e-07)	(6.88e-07)
nd_perth	3.55e-07	3.59e-07	3.80e-07	4.90e-07
	(1.37e-06)	(1.37e-06)	(1.37e-06)	(1.37e-06)
urban	-0.00743**	-0.00740**	-0.00743**	-0.00768**
	(0.00346)	(0.00347)	(0.00346)	(0.00348)
nd_forest	6.14e-06**	6.12e-06**	6.07e-06**	6.14e-06**
	(3.09e-06)	(3.09e-06)	(3.09e-06)	(3.09e-06)
nd_wetland	2.31e-07	2.29e-07	2.42e-07	2.59e-07
	(1.94e-07)	(1.94e-07)	(1.91e-07)	(1.93e-07)
nd_beach	-1.10e-08	-1.32e-08	1.47e-08	6.81e-08

Table 1.9.3: Estimations Results for Model 2B

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(3.08e-07)	(3.07e-07)	(2.99e-07)	(3.10e-07)
nd_sandycoastline	-6.42e-08	-6.15e-08	-8.92e-08	-1.46e-07
	(3.24e-07)	(3.23e-07)	(3.15e-07)	(3.27e-07)
nd_fstation	-1.61e-06*	-1.61e-06*	-1.62e-06*	-1.62e-06*
	(9.69e-07)	(9.69e-07)	(9.69e-07)	(9.69e-07)
2011	-0.0439***	-0.0439***	-0.0439***	-0.0439***
	(0.00628)	(0.00628)	(0.00628)	(0.00628)
2012	-0.0538***	-0.0538***	-0.0538***	-0.0538***
	(0.00595)	(0.00595)	(0.00595)	(0.00595)
2013	-0.0643***	-0.0643***	-0.0643***	-0.0643***
	(0.00572)	(0.00572)	(0.00572)	(0.00572)
2014	-0.0506***	-0.0506***	-0.0506***	-0.0506***
	(0.00577)	(0.00577)	(0.00577)	(0.00577)
2015	-0.0873***	-0.0874***	-0.0874***	-0.0874***
	(0.00593)	(0.00593)	(0.00593)	(0.00593)
2016	-0.0716*	-0.0708*	-0.0711*	-0.0710*
	(0.0404)	(0.0404)	(0.0404)	(0.0404)
2017	-0.114***	-0.113***	-0.114***	-0.113***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2018	-0.147***	-0.146***	-0.146***	-0.146***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2019	-0.142***	-0.142***	-0.142***	-0.142***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
Constant	12.63***	12.63***	12.63***	12.63***
	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Observations	51,055	51,055	51,055	51,055
R-squared	0.614	0.614	0.614	0.614
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

APPENDIX B: ADDITIONAL RESULTS

Table 1.9.4: Estimations Results for Model 2C

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Fire	-0.0667*	-0.0669*	-0.0661	-0.0664*
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
evacuation_directed	-0.0729*	-0.0731*	-0.0807**	-0.0789**
	(0.0401)	(0.0391)	(0.0380)	(0.0371)
Fire#evacuation_directed	-0.0121	0.00122	0.0452	0.0347
	(0.0573)	(0.0554)	(0.0522)	(0.0505)
Proximity	-0.00528	-0.00484	0.000956	-6.89e-05

Table 1.9.4: Estimations Results for Model 2C

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.0175)	(0.0155)	(0.0120)	(0.00978)
Fire#Proximity	0.0468	0.0335	-0.0110	-0.000341
	(0.0310)	(0.0272)	(0.0199)	(0.0150)
AreaSize	8.44e-07***	8.44e-07***	8.44e-07***	8.45e-07***
	(6.13e-08)	(6.13e-08)	(6.13e-08)	(6.13e-08)
Baths	0.155***	0.155***	0.155***	0.155***
	(0.00311)	(0.00311)	(0.00311)	(0.00311)
Bedrooms	0.0657***	0.0657***	0.0657***	0.0657***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
HasStudy	0.0921***	0.0921***	0.0921***	0.0921***
	(0.00314)	(0.00314)	(0.00314)	(0.00314)
HasSeparateDining	0.000253	0.000275	0.000199	0.000218
	(0.00568)	(0.00568)	(0.00568)	(0.00568)
HasFamilyRoom	0.0465***	0.0465***	0.0465***	0.0465***
	(0.00321)	(0.00321)	(0.00321)	(0.00321)
HasSunroom	-0.00170	-0.00171	-0.00183	-0.00178
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
HasRumpusRoom	0.00896**	0.00897**	0.00890*	0.00891*
	(0.00455)	(0.00455)	(0.00455)	(0.00455)
HasFireplace	0.0151***	0.0151***	0.0151***	0.0151***
	(0.00498)	(0.00498)	(0.00498)	(0.00498)
HasWalkInWardrobe	0.00722*	0.00719*	0.00716*	0.00717*
	(0.00426)	(0.00426)	(0.00426)	(0.00426)
HasCourtyard	-0.00508	-0.00508	-0.00507	-0.00508
	(0.00600)	(0.00600)	(0.00600)	(0.00600)
HasInternalLaundry	0.0277***	0.0277***	0.0277***	0.0277***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
HasHeating	0.00987**	0.00989**	0.00986**	0.00987**
	(0.00496)	(0.00496)	(0.00496)	(0.00496)
HasAirConditioning	-0.00671**	-0.00673**	-0.00677**	-0.00676**
	(0.00289)	(0.00289)	(0.00289)	(0.00289)
HasBalcony	0.153***	0.153***	0.153***	0.153***
	(0.00520)	(0.00520)	(0.00520)	(0.00520)
HasBarbeque	0.0187***	0.0187***	0.0187***	0.0187***
	(0.00598)	(0.00598)	(0.00598)	(0.00598)
HasPolishedTimberFloor	0.0346***	0.0346***	0.0347***	0.0346***
	(0.00627)	(0.00627)	(0.00627)	(0.00627)
HasEnsuite	0.0176***	0.0176***	0.0177***	0.0177***
	(0.00363)	(0.00363)	(0.00363)	(0.00363)
HasSpa	0.0541***	0.0541***	0.0541***	0.0541***
	(0.00566)	(0.00566)	(0.00566)	(0.00566)
HasGarage	0.0945***	0.0945***	0.0945***	0.0945***
	(0.00292)	(0.00292)	(0.00292)	(0.00292)
HasLockUpGarage	-0.0237***	-0.0237***	-0.0237***	-0.0237***
	(0.00565)	(0.00565)	(0.00565)	(0.00565)
HasPool	0.108***	0.108***	0.108***	0.108***
	(0.00456)	(0.00456)	(0.00456)	(0.00456)
HasTennisCourt	0.0728**	0.0728**	0.0727**	0.0727**

Table 1.9.4: Estimations Results for Model 2C

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.0339)	(0.0339)	(0.0339)	(0.0339)
HasAlarm	0.0878***	0.0878***	0.0878***	0.0878***
	(0.00626)	(0.00626)	(0.00626)	(0.00626)
Apartment House	0.468***	0.468***	0.468***	0.468***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Cottage	-0.260***	-0.260***	-0.260***	-0.260***
	(0.0658)	(0.0658)	(0.0658)	(0.0658)
Duplex	-0.0955***	-0.0955***	-0.0954***	-0.0954***
	(0.00839)	(0.00839)	(0.00839)	(0.00839)
Flat	-0.332***	-0.332***	-0.332***	-0.332***
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Patio House	-0.160**	-0.160**	-0.160**	-0.160**
	(0.0750)	(0.0750)	(0.0750)	(0.0750)
Quadruplex	0.0188	0.0189	0.0189	0.0189
	(0.129)	(0.129)	(0.129)	(0.129)
Semi	-0.0134	-0.0134	-0.0135	-0.0135
	(0.102)	(0.102)	(0.102)	(0.102)
Terrace	0.0131	0.0131	0.0128	0.0129
	(0.0834)	(0.0834)	(0.0834)	(0.0834)
Townhouse	-0.0746***	-0.0746***	-0.0747***	-0.0746***
	(0.00702)	(0.00702)	(0.00702)	(0.00702)
Triplex	0.370***	0.370***	0.370***	0.370***
	(0.110)	(0.110)	(0.110)	(0.110)
Unit	-0.130***	-0.130***	-0.130***	-0.130***
	(0.00633)	(0.00633)	(0.00633)	(0.00633)
Villa	-0.370***	-0.370***	-0.370***	-0.370***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)
Villa House	-0.177***	-0.177***	-0.176***	-0.176***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)
nd_bus_standard	-1.39e-07	-1.40e-07	-1.35e-07	-1.39e-07
	(1.66e-07)	(1.66e-07)	(1.66e-07)	(1.67e-07)
nd_bus_cat	-5.05e-07	-5.08e-07	-3.67e-07	-4.36e-07
	(1.72e-06)	(1.72e-06)	(1.73e-06)	(1.74e-06)
nd_rail	-9.99e-08	-1.04e-07	-1.51e-07	-1.30e-07
	(4.19e-07)	(4.21e-07)	(4.25e-07)	(4.26e-07)
nd_cas	1.03e-06	1.01e-06	1.06e-06	1.03e-06
	(7.06e-07)	(7.07e-07)	(7.11e-07)	(7.70e-07)
nd_perth	5.61e-07	5.66e-07	4.68e-07	5.18e-07
	(1.35e-06)	(1.36e-06)	(1.37e-06)	(1.37e-06)
urban	-0.00704**	-0.00709**	-0.00723**	-0.00719**
	(0.00347)	(0.00347)	(0.00346)	(0.00346)
nd_forest	5.91e-06*	5.87e-06*	5.91e-06*	5.88e-06*
	(3.09e-06)	(3.09e-06)	(3.09e-06)	(3.09e-06)
nd_wetland	2.73e-07	2.77e-07	2.84e-07	2.84e-07
	(1.93e-07)	(1.93e-07)	(1.92e-07)	(1.93e-07)
nd_beach	1.08e-07	1.20e-07	1.37e-07	1.35e-07
	(3.08e-07)	(3.07e-07)	(3.04e-07)	(3.07e-07)
nd_sandycoastline	-1.86e-07	-1.97e-07	-2.19e-07	-2.15e-07

Table 1.9.4: Estimations Results for Model 2C

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(3.25e-07)	(3.24e-07)	(3.21e-07)	(3.23e-07)
nd_fstation	-1.60e-06*	-1.62e-06*	-1.70e-06*	-1.67e-06*
	(9.66e-07)	(9.66e-07)	(9.68e-07)	(9.65e-07)
2011	-0.0439***	-0.0438***	-0.0438***	-0.0438***
	(0.00628)	(0.00628)	(0.00628)	(0.00628)
2012	-0.0538***	-0.0538***	-0.0538***	-0.0538***
	(0.00595)	(0.00595)	(0.00595)	(0.00595)
2013	-0.0643***	-0.0643***	-0.0642***	-0.0642***
	(0.00571)	(0.00571)	(0.00572)	(0.00572)
2014	-0.0505***	-0.0505***	-0.0504***	-0.0504***
	(0.00577)	(0.00577)	(0.00577)	(0.00577)
2015	-0.0873***	-0.0873***	-0.0873***	-0.0873***
	(0.00593)	(0.00593)	(0.00593)	(0.00593)
2016	-0.0713*	-0.0711*	-0.0713*	-0.0713*
	(0.0404)	(0.0404)	(0.0404)	(0.0404)
2017	-0.114***	-0.114***	-0.114***	-0.114***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2018	-0.146***	-0.146***	-0.146***	-0.146***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2019	-0.142***	-0.142***	-0.142***	-0.142***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
Constant	12.63***	12.63***	12.63***	12.63***
	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Observations	51,055	51,055	51,055	51,055
R-squared	0.614	0.614	0.614	0.614
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

Table 1.9.5: Estimation Results for Model 2D

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
Fire	-0.0663	-0.0669*	-0.0665*	-0.0666*
	(0.0403)	(0.0403)	(0.0403)	(0.0403)
evacuation_all	-0.00433	-0.00327	-0.00458	-0.00687
	(0.0170)	(0.0174)	(0.0221)	(0.0190)
Fire#evacuation_all	-0.0604**	-0.0646**	-0.0663*	-0.0596*
	(0.0283)	(0.0291)	(0.0365)	(0.0316)
Proximity	-0.0168	-0.0137	-0.00364	-0.000273
	(0.0163)	(0.0151)	(0.0152)	(0.0110)
Fire#Proximity	0.0566**	0.0516**	0.0242	0.0180
	(0.0273)	(0.0255)	(0.0249)	(0.0168)
AreaSize	8.44e-07***	8.44e-07***	8.44e-07***	8.44e-07***

Table 1.9.5: Estimation Results for Model 2D

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(6.13e-08)	(6.13e-08)	(6.13e-08)	(6.13e-08)
Baths	0.155***	0.155***	0.155***	0.155***
	(0.00311)	(0.00311)	(0.00311)	(0.00311)
Bedrooms	0.0657***	0.0657***	0.0657***	0.0657***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
HasStudy	0.0921***	0.0921***	0.0921***	0.0922***
	(0.00314)	(0.00314)	(0.00314)	(0.00314)
HasSeparateDining	0.000268	0.000323	0.000298	0.000303
	(0.00568)	(0.00568)	(0.00568)	(0.00568)
HasFamilyRoom	0.0465***	0.0465***	0.0465***	0.0465***
	(0.00321)	(0.00321)	(0.00321)	(0.00321)
HasSunroom	-0.00187	-0.00186	-0.00190	-0.00189
	(0.0115)	(0.0115)	(0.0115)	(0.0115)
HasRumpusRoom	0.00887*	0.00889*	0.00885*	0.00886*
	(0.00455)	(0.00455)	(0.00455)	(0.00455)
HasFireplace	0.0151***	0.0151***	0.0151***	0.0151***
	(0.00498)	(0.00498)	(0.00498)	(0.00498)
HasWalkInWardrobe	0.00719*	0.00717*	0.00716*	0.00715*
	(0.00426)	(0.00426)	(0.00426)	(0.00426)
HasCourtyard	-0.00499	-0.00500	-0.00499	-0.00499
	(0.00600)	(0.00600)	(0.00600)	(0.00600)
HasInternalLaundry	0.0278***	0.0278***	0.0278***	0.0278***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
HasHeating	0.00981**	0.00984**	0.00983**	0.00984**
	(0.00495)	(0.00495)	(0.00496)	(0.00496)
HasAirConditioning	-0.00667**	-0.00668**	-0.00670**	-0.00670**
	(0.00289)	(0.00289)	(0.00289)	(0.00289)
HasBalcony	0.153***	0.153***	0.153***	0.153***
	(0.00520)	(0.00520)	(0.00520)	(0.00520)
HasBarbeque	0.0187***	0.0187***	0.0187***	0.0186***
	(0.00598)	(0.00598)	(0.00598)	(0.00598)
HasPolishedTimberFloor	0.0348***	0.0348***	0.0348***	0.0347***
	(0.00627)	(0.00627)	(0.00627)	(0.00627)
HasEnsuite	0.0176***	0.0176***	0.0177***	0.0177***
	(0.00363)	(0.00363)	(0.00363)	(0.00363)
HasSpa	0.0542***	0.0542***	0.0542***	0.0542***
	(0.00566)	(0.00566)	(0.00566)	(0.00566)
HasGarage	0.0945***	0.0945***	0.0945***	0.0945***
	(0.00292)	(0.00292)	(0.00292)	(0.00292)
HasLockUpGarage	-0.0238***	-0.0238***	-0.0238***	-0.0238***
	(0.00565)	(0.00565)	(0.00565)	(0.00565)
HasPool	0.108***	0.108***	0.108***	0.108***
	(0.00456)	(0.00456)	(0.00456)	(0.00456)
HasTennisCourt	0.0733**	0.0733**	0.0732**	0.0732**
	(0.0339)	(0.0339)	(0.0339)	(0.0339)
HasAlarm	0.0879***	0.0879***	0.0879***	0.0878***
	(0.00626)	(0.00626)	(0.00626)	(0.00626)
Apartment House	0.468***	0.468***	0.468***	0.468***

Table 1.9.5: Estimation Results for Model 2D

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Cottage	-0.260***	-0.260***	-0.259***	-0.259***
	(0.0658)	(0.0658)	(0.0658)	(0.0658)
Duplex	-0.0953***	-0.0953***	-0.0953***	-0.0953***
	(0.00839)	(0.00839)	(0.00839)	(0.00839)
Flat	-0.332***	-0.332***	-0.331***	-0.331***
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
Patio House	-0.160**	-0.160**	-0.160**	-0.160**
	(0.0750)	(0.0750)	(0.0750)	(0.0750)
Quadruplex	0.0188	0.0189	0.0189	0.0190
	(0.129)	(0.129)	(0.129)	(0.129)
Semi	-0.0127	-0.0127	-0.0128	-0.0127
	(0.102)	(0.102)	(0.102)	(0.102)
Terrace	0.0129	0.0129	0.0129	0.0129
	(0.0834)	(0.0834)	(0.0834)	(0.0834)
Townhouse	-0.0747***	-0.0746***	-0.0746***	-0.0746***
	(0.00702)	(0.00702)	(0.00702)	(0.00702)
Triplex	0.370***	0.370***	0.370***	0.370***
	(0.110)	(0.110)	(0.110)	(0.110)
Unit	-0.130***	-0.130***	-0.130***	-0.130***
	(0.00633)	(0.00633)	(0.00633)	(0.00633)
Villa	-0.370***	-0.370***	-0.370***	-0.370***
	(0.0443)	(0.0443)	(0.0443)	(0.0443)
Villa House	-0.177***	-0.177***	-0.177***	-0.177***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)
nd_bus_standard	-8.18e-08	-8.20e-08	-8.69e-08	-9.60e-08
	(1.66e-07)	(1.66e-07)	(1.66e-07)	(1.66e-07)
nd_bus_cat	-6.36e-08	-8.24e-08	-1.48e-07	-2.48e-07
	(1.73e-06)	(1.73e-06)	(1.73e-06)	(1.75e-06)
nd_rail	-1.96e-07	-1.89e-07	-1.71e-07	-1.47e-07
	(4.22e-07)	(4.23e-07)	(4.25e-07)	(4.26e-07)
nd_cas	4.80e-07	4.68e-07	4.88e-07	3.38e-07
	(6.27e-07)	(6.28e-07)	(6.20e-07)	(6.75e-07)
nd_perth	2.20e-07	2.32e-07	2.81e-07	3.57e-07
	(1.36e-06)	(1.36e-06)	(1.37e-06)	(1.38e-06)
urban	-0.00707**	-0.00704**	-0.00698**	-0.00714**
	(0.00347)	(0.00347)	(0.00348)	(0.00346)
nd_forest	6.32e-06**	6.32e-06**	6.30e-06**	6.36e-06**
	(3.09e-06)	(3.09e-06)	(3.09e-06)	(3.09e-06)
nd_wetland	2.13e-07	2.11e-07	2.14e-07	2.28e-07
	(1.94e-07)	(1.94e-07)	(1.93e-07)	(1.92e-07)
nd_beach	-3.65e-08	-4.12e-08	-3.19e-08	6.71e-09
	(3.08e-07)	(3.06e-07)	(3.02e-07)	(3.01e-07)
nd_sandycoastline	-4.82e-08	-4.26e-08	-5.10e-08	-9.24e-08
	(3.23e-07)	(3.22e-07)	(3.17e-07)	(3.16e-07)
nd_fstation	-1.67e-06*	-1.66e-06*	-1.64e-06*	-1.64e-06*
	(9.68e-07)	(9.68e-07)	(9.67e-07)	(9.64e-07)
2011	-0.0439***	-0.0439***	-0.0439***	-0.0439***

Table 1.9.5: Estimation Results for Model 2D

VARIABLES	(1) 0-2 km lnPrice	(2) 0-5 km lnPrice	(3) 0-10 km lnPrice	(4) 0-20 km lnPrice
	(0.00628)	(0.00628)	(0.00628)	(0.00628)
2012	-0.0538***	-0.0538***	-0.0538***	-0.0538***
	(0.00595)	(0.00595)	(0.00595)	(0.00595)
2013	-0.0643***	-0.0643***	-0.0643***	-0.0643***
	(0.00571)	(0.00571)	(0.00571)	(0.00571)
2014	-0.0506***	-0.0506***	-0.0506***	-0.0506***
	(0.00577)	(0.00577)	(0.00577)	(0.00577)
2015	-0.0874***	-0.0874***	-0.0874***	-0.0874***
	(0.00593)	(0.00593)	(0.00593)	(0.00593)
2016	-0.0714*	-0.0708*	-0.0711*	-0.0712*
	(0.0404)	(0.0404)	(0.0404)	(0.0404)
2017	-0.114***	-0.113***	-0.113***	-0.114***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2018	-0.146***	-0.146***	-0.146***	-0.146***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
2019	-0.142***	-0.141***	-0.142***	-0.142***
	(0.0408)	(0.0408)	(0.0408)	(0.0408)
Constant	12.63***	12.63***	12.63***	12.63***
	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Observations	51,055	51,055	51,055	51,055
R-squared	0.614	0.614	0.614	0.614
Suburb FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

APPENDIX C: DATA

Table 1.9.6: Data sources

Variable	Source	Name of dataset/file	Format
sale price (AUD)	APM	-	Excel
		structural attributes	
area (m2)	APM	-	Excel
bathrooms	APM	-	Excel
bedrooms	APM	-	Excel
'Has' attributes	APM	-	Excel
		location of environmental attributes	
public beach	Google Earth Pro	-	Website
forest	Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES)	Forests of Australia (2018)	Raster (ESRI grid)

Table 1.9.6: Data sources

Variable	Source	Name of dataset/file	Format
Waroona burn scar	Department of Biodiversity, Conservation and Attractions	DBCA Fire History (DBCA-060)	shapefile
		location of neighbourhood attributes	
bus stop	Public Transport Authority	Public Transport Authority Stops (PTA-001)	shapefile
rail stop	Public Transport Authority	Public Transport Authority Stops (PTA-001)	shapefile
current active school	Department of Education	Current Active Schools Semester 1 2013 - Public (DET-004) Current Active Schools Semester 1 2014 - Public (DET-006) Current Active Schools Semester 1 2015 - Public (DET-008) Current Active Schools Semester 1 2016 - Public (DET-012) Current Active Schools Semester 1 2017 - Public (DET-014) Current Active Schools Semester 1 2018 - Public (DET-016) Current Active Schools Semester 1 2019 - Public (DET-017)	shapefile
Perth townsite	Landgate	Townsites (LGATE-248)	shapefile
urban land	Landgate	Townsites (LGATE-248)	shapefile
		location of risk-moderating attributes	
sandy coastline	GeoScience Australia	Geomorphology Smartline ESRI File Geodatabase	Geodatabase
urban land	Landgate	Townsites (LGATE-248)	shapefile
fire station	Department of Fire and Emergency Services	DFES Stations (DFES-023)	shapefile
		spatial information on emergency warning alerts	
ewalert, ewalert2	Government of Western Australia	Report of the Special Inquiry into the January 2016 Waroona Fire	PDF text
-	Landgate	Localities (LGATE-234)	shapefile
-	Geofabrik	australia-latest-osm	Open Street Map (OSM)

Table 1.9.7: Summary statistics

Variable	Unit	Obs	Mean	Std. dev.	Min	Max
			dependent variable			
sale price	AUD	51,055	424,625	230,049	40,000	6,050,000
			environmental attributes[a]			
forest	metres	51,055	514	465	0	3,241
wetland	metres	51,055	11,510	12,492	0	75,570
beach	metres	51,055	12,321	18,432	68	122,454
			neighbourhood attributes[a]			
bus	metres	51,055	6,933	18,806	10	143,717

Table 1.9.7: Summary statistics

Variable	Unit	Obs	Mean	Std. dev.	Min	Max
rail	metres	51,055	65,080	60,377	99	291,100
cas	metres	51,055	1,349	2,255	0	36,965
perth	metres	51,055	121,276	63,966	21,536	345,033
			risk moderating attributes[a]			
sandycoastline	metres	51,055	10,191	15,770	23	99,198
fstation	metres	51,055	2,441	1,537	16	24,158
forest	metres	51,055	514	465	0	3,241
			proximity to burn scar			
burn scar	metres	51,055	49,250	31,533	14	230,883

[a] euclidean distance to nearest attribute in metres

Table 1.9.8: Property type frequency

Property type	Frequency	Percent
Apartment House	429	0.84
Cottage	25	0.05
Duplex	1,304	2.55
Flat	103	0.20
House	43,849	85.89
Patio House	15	0.03
Quadruplex	5	0.01
Semi	8	0.02
Terrace	12	0.02
Townhouse	1,978	3.87
Triplex	7	0.01
Unit	2,798	5.48
Villa	44	0.09
Villa House	478	0.94
Total	51,055	100

CHAPTER 2 WILDFIRE RISK AND PROPERTY PRICES: A DISCONTINUITY ANALYSIS OF THE INTRODUCTION OF BUSHFIRE PRONE AREA MAPS

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ABSTRACT

We investigate the impact of wildfire risk-exposure information shocks on preferences for safety with evidence from the housing market. More precisely, we study the introduction of wildfire risk maps, colloquially known as *bushfire prone area* maps, in Western Australia in 2015. Using an extensive dataset on property market transactions and high-resolution geographic information system data, we set a regression discontinuity design to investigate the price differential for properties located across the hazard discontinuity introduced by the maps. The results indicate that properties within bushfire prone areas are sold at a price 4.2% lower than those outside. Our analysis suggest that this discount is driven by a pure information shock that increases preference for safety, and not by pre-determined risk perception or the implementation of more stringent building regulations for risk-exposed properties.

Keywords: wildfires, risk, information shock, housing market, regression discontinuity

JEL codes: Q51, Q54, D80, R20

2.1 INTRODUCTION

Wildfires put lives and livelihoods at risk, with potential impacts on health, infrastructure, and ecosystem services (UNEP, 2022). As climate, land-use, and land management practices change, so does wildfire risk. For instance, some areas around the world will experience higher frequency in wildfires, including unexpected areas, and it is predicted that by the end of this century, the likelihood of catastrophic wildfires will be 1.31 to 1.57 times higher (UNEP, 2022). For this reason, it is crucial that we understand the socioeconomic costs – or benefits – of being directly or indirectly affected by wildfire events, landscape management practices, or related policies and regulations. There is a growing and urgent need to work on understanding how communities and policy makers respond to wildfires and how this response translates into society's wellbeing.

A considerable number of hedonic studies investigate the effect of nearby wildfires on property prices. Surprisingly however, there is almost a complete absence of studies looking at the capitalisation of geographic regulations related to wildfire risk. In this study we use property prices for the period 2010-2019 to investigate the effect of a particular wildfire risk management policy: the introduction of wildfire risk maps in Western Australia (WA) in 2015 - known as bushfire prone area (BPA) maps. We argue that the introduction of these maps, and the subsequent editions, provide an information update for households, and that the impact on property prices reveals the change in households' beliefs concerning wildfire safety. Assessing the impact of these information updates (and associated regulatory changes) following the introduction of these maps is highly relevant given that wildfires are expected to occur more frequently due to climate change and generate high damage and suppression costs.

The designation of BPAs creates a geographic discontinuity that divides owners of properties within the boundary of a BPA from those outside. Those within the boundary are essentially confronted by the following. First, an information shock. It is documented in local news that the introduction of BPAs generated a surprise among Western Australians as they found out that around 90 percent of WA is *bushfire prone*. Second, more stringent planning and building regulations, which created expectations of higher building costs. Third, the expectation of higher insurance premiums within BPAs. These first three practical aspects of the BPA designation are documented in de Ceglie (2015). Lastly, for buyers and sellers, it came with the expectation that real estate agents should and will inform parties of the BPA designation status of the property on sale (Department of Commerce, 2016).

We exploit the geographic discontinuity created by the map by using a sharp regression discontinuity design (RDD) to estimate the impact of BPA maps on property prices. Our literature review reveals that we are, surprisingly, not only among the first to study wildfire risk maps in Australia, but also the first to study the introduction of wildfire risk maps under an RDD setting anywhere. We also attempt to disentangle pre-determined risk perception – i.e., wildfire risk perceptions formed prior to the introduction of BPA maps – from risk updates, in an RDD setting.

To identify the treatment effect, we implement a local polynomial point estimation technique that uses only those observations in the neighbourhood of the BPA boundary where the risk of wildfire is essentially, the same. This neighbourhood is defined by a mean squared error (MSE) optimal bandwidth, given a polynomial of order 1 and kernel weights defined by a triangular kernel function that assigns higher weights to observations nearest to the boundary. Critically, we implement the local polynomial point estimation in two different periods: first, for the pre-mapping period of 1st January 2010 to 7th December 2015 where the RD treatment effect reflects the impact of prior differences in risk perceptions on property prices and second, for the mapping period of 8th December 2015 to 31st December 2019 where the RD treatment effect includes the 'BPA effect', i.e., the impact of BPA maps and associated regulations on property prices. For the first period, we encounter no significant RD treatment effect suggesting that our results are not driven by pre-determined risk perceptions. However, once the maps are introduced, properties within the BPA are sold at a significant discount. These results are robust to different bandwidth choices, suggesting that the chosen bandwidth is not driving the results, and our results reveal no evidence of the manipulation of treatment assignment in the proximity of the BPA boundary.

Our findings strongly suggest that individuals are paying a premium for reduced exposure to wildfire risk, further suggesting that the implicit value of safety is higher when the set of information on wildfire risk expands, i.e., when risk maps are introduced. By conducting the RD analysis for the pre-treatment period, we confirm that preferences for safety did not significantly differ between BPAs and non-BPAs before the introduction of risk maps, enabling us to fully attribute our results to the introduction of BPA maps. This information is sensitive for policy makers for several reasons. First, it suggests that the BPA mapping policy is effective in shifting housing preferences away from risky areas, and it therefore has the potential to reduce management, suppression, and recovery costs from wildfire events. Second, it suggests that, as climate change increases the likelihood and intensity of wildfires, the housing market in non-BPAs might become more expensive over time, increasing the risk exposure of lower-income households and exacerbating social inequality. Lastly, given that BPA designation directly depends on the presence of bushfire prone vegetation (BPV), it suggests that revegetation programs, such as those implemented by Main Roads Australia (mainroads, n.d.), have a direct cost on people's wealth and wellbeing that policy makers must account for.

The remainder of the paper is organised as follows: Section 2.2 reviews the existing literature of RDD studies looking at the impact of geographical discontinuities on property prices, Section 2.3 outlines the theory of the RDD methodology and formalizes the design of our study, Section 2.4 presents a brief overview of the data and summary statistics, and Section 2.5 presents the results followed by a discussion, validation tests and conclusions in Sections 2.6, 2.7 and 2.8 respectively.

2.2 LITERATURE REVIEW

Previous hedonic studies on the issue of wildfire risk usually focus on identifying the information shock from the occurrence of previous fires (e.g., Loomis, 2004; Mueller & Loomis, 2008; Mueller et al., 2009; Hansen & Naughton, 2013; Kiel & Matheson, 2018; McCoy & Walsh, 2018).

However, there is almost a complete absence of studies investigating the effect of zoning policies related to wildfire risk management (such as BPA maps) despite the existence of a considerable number of hedonic studies analysing the impact of maps related to other spatially delineated risks such as flooding (e.g., Shr & Zipp, 2019; Atreya & Czajkowski, 2019; Daniel et al., 2009) and earthquakes (e.g., Brookshire et al., 1985; Nakagawa et al., 2007; Hidano et al., 2015).

Given the scarce evidence on the effect of wildfire risk maps on property prices, our literature review focuses on previous hedonic applications using RDD models to estimate the effect of spatially delineated policies. This literature can be divided into three groups: i) studies focusing on the effect of regulations constricted to a geographical boundary; ii) studies looking at geographical discontinuities in the provision of environmental quality/amenities; and iii) an emerging branch of research that is closest to our paper and focuses on analysing the impact of natural disaster risk zoning on property prices.

The group of studies analysing regulations constricted to a geographical boundary usually refer to the introduction of policies that result in more stringent regulations for properties located within the area of influence of the policy. These studies compare the prices of properties around the policy boundary that determines the regression discontinuity line. Grout et al. (2011) is, to the best of our knowledge, the first study to implement a RDD for the impact of land-use regulations of any kind. The analysis focuses on the effect of the designation of the Urban Growth Boundary (UGB) in Portland, Oregon, United States (US) in 2008. Parcels of land within the UGB are zoned for intensive purposes (e.g., high-density residential housing, commercial or industrial uses) whilst parcels of land outside the UGB are zoned for non-intensive purposes (e.g., agriculture, forestry, and exceptionally, for low-density residential developments).

Other studies on the impact of geographically delimited regulations include Koster et al. (2012) on the impact of more stringent and binding housing restrictions to protect pre-World War II heritage buildings in Rotterdam, Netherlands; Turner, et al. (2014) on the impact of level of land use regulation in US on land price and welfare (decomposed in the effects on the own-lot, nearby land, and supply of developable land); Koster et al. (2021) on the impact of regulatory restrictions applied to the market of short-term rental online platforms in Los Angeles, US; Cooper & Namit (2021) on the impact of a viewshafts regulations in the central business district of Auckland, New Zealand; and Ferreira et al. (2021) on the impact of the 2016 reform on maximum permitted construction on city blocks of Sao Paulo, Brazil. In all cases, the running variable for the RDD is given by the distance from the location of the property to the policy boundary, and the outcome variable is usually given by a measure of value for properties/parcels located around the policy boundary. Except for Ferreira et al. (2021), all of these studies suggest that stringent regulations have a negative impact on house prices/rents (land values for Turner, et al. (2014)). The study by Ferreira et al. (2021) is slightly different, as they analyse the effect of relaxing restrictions on maximum permitted construction units on the number of multi-family construction buildings. The authors find that developers filed more multi-family construction permits in city-blocks with higher allowable densities, leading to an increase in housing stock and a decrease in property prices.

A second strand of the RDD literature focuses on the impact of environmental quality or environmental amenities on property prices. This group of studies include a paper by Greenstone & Gallagher (2008) on consumers' valuation of the 'Superfund' program for hazardous waste sites clean-ups in the US, and studies by Chay & Greenstone (2005), Huang & Lanz (2018), and Liu et al. (2021) on the impact of air quality discontinuities on house prices. The running variable for these studies is given by a threshold value on a variable that identifies properties subject to a discontinuous change in environmental quality: points on the Hazardous Ranking System (HRS) for the case of hazardous waste clean-ups, and total suspended particulates (TSPs) concentration or distance to the Huai River in China for the studies on air quality.

Greenstone & Gallagher (2008) compare residential property prices, among other variables, for the period 1980 – 2000 for two types of areas: those surrounding the 400 hazardous waste sites selected for the 'Superfund' program (based on HRS score) and those surrounding the 290 hazardous waste sites that narrowly missed program selection. The authors run a hedonic regression analysis on median property values taken from census data from the year 2000. The results from the RDD analysis suggest a price increase for properties located close to eligible sites. However, the authors conclude that residents' willingness to pay (WTP) to avoid hazardous waste sites is low and the programme's costs are likely to exceed its benefits.

Regarding the studies on air quality discontinuities, Chay & Greenstone (2005) study the Clean Air Act Amendments (CAAA) of 1970 in the US. Under the CAAA, counties that exceed federal ceilings on air pollution concentrations (based on TSPs) are designated as 'nonattainment' by the Environmental Protection Agency and face strict regulations. The authors conclude that the CAAA is associated with declines in air pollution and increasing housing prices for nonattainment counties. On the other hand, Huang & Lanz (2018), and Liu et al. (2021) study the impact of air quality discontinuities in China arising from the Huai River policy on house prices. This policy subsidised heavily coal dependent winter heating in the area north of the Huai River, thereby contributing to air pollution in northern China. Huang & Lanz (2018) use a fuzzy RDD model to show that the policy successfully explains air pollution differences near the Huai River boundary and find a negative and statistically significant relationship between property prices and PM_{10} concentration. Liu et al. (2021) use city-level panel data for the period 2006-2015 including residential house prices and PM_{10} concentrations for 30 Chinese cities located within 7° latitude of the Huai River. The results suggest that, at the threshold, PM_{10} increases by 41 μg/m3 and house prices decrease by 42%.

Finally, this study contributes to an emerging branch of literature using RDD to analyse the impact of natural disaster risk zoning on property prices. To the best of our knowledge, the paper by Hidano et al. (2015) on earthquake risk is the first one in this category. The authors study the causal impact of information on seismic hazard risk on property sale prices for the 23 wards of Tokyo's residential market between 2008 and 2012. For this purpose, the authors implement a RDD where the causal impact is triggered by the information on geographical boundaries for high-risk zones. In other words, the authors aim to identify the market's reaction to the information on geographical boundaries that enclose high-risk zones. The authors report results on average risk-reduction effects conditional on age; as the property's age increases, so do the benefits of reducing the risk score, meaning that households attach a higher value to buildings that comply with the newest building regulations and therefore more capable of resisting earthquake damage. The (unconditional) average risk reduction effect is positive and statistically significant. Overall, results indicate that prices are higher in low-risk zones. Given that insurance fee is uniform across safe and risky zones, the price difference is interpreted as the value of self-insurance.

Tangentially related to our research is Donovan et al. (2007)'s study on wildfire risk ratings in wildland urban interface (WUI) areas in Colorado Springs, US. Interestingly, the areas studied were free from wildfires since 1950, despite the fact that the areas received no fuel treatment to reduce wildfire risk. Due to the absence of fuel treatment, the authors follow the assumption that amenity values are constant throughout the study period. Using 9,903 properties sold between 1998-2004 and the HPM, the authors evaluate the change in property prices after the wildfire risk ratings were communicated through the Colorado Springs Fire Department website in the year 2000. Parcels were wildfire risk-rated as low, moderate, high, very high, or extreme. The authors find that before risk ratings were communicated, forest amenities were valued higher than wildfire risk. In other words, for the pre-treatment period, property prices were larger for properties who would later on have higher risk ratings. After risk ratings were communicated, this positive relationship is no longer significant. This suggests an increased risk awareness. However, the effect is short-lived. Additionally, the authors note that the increased risk awareness may have been caused not by wildfire risk ratings per se, but by the Hayman fire in 2002, which destroyed 132 homes just 20 miles (approx. 32 km) away from the study area. This fire could have encouraged residents to use the website provided.

The study closest to our research – because they study BPAs under a methodology similar to ours - is that of Mo Koo & Liang (2022) on the impact of wildfire risk and salience on the price of properties in the state of Victoria, Australia for the period 2014-2018. First, the authors estimate a hedonic price function (HPF) to test for the impact of bushfire risk specific to the property location by comparing outcomes on sale prices for properties located within bushfire prone areas (BPAs) to those outside BPAs. To control for risk level heterogeneity, the authors restrict the sample to properties within 300-metre buffer zones inside and outside the boundary. Results for this first analysis suggest properties located within BPAs are more highly valued than those located outside BPAs, with a price mark-up of 1.61-1.89%. Nonetheless, house prices within

BPAs are found to be susceptible to bushfire events: following the bushfire season of 2015/16, prices of houses within a BPA decreased by about 0.9-1.7% which is persistent even after two years.

It is important to highlight that Mo Koo and Liang (2022) do not follow conventional procedures for an RDD. Instead, the authors simply restrict the sample to those observations within 300-metres from the BPA boundary. This bandwidth is not necessarily the MSE-optimal choice, but a discretionary one that intends to reduce risk heterogeneity between properties within and outside BPAs. Furthermore, their difference-in-differences (DD) analysis is defined by the 2015/16 bushfire season and not by the introduction of BPA maps, therefore, Mo Koo & Liang (2022) do not look at the effect from the *introduction* of BPA maps per se, but rather at the risk saliency effect of the 2015/16 bushfire season on two groups: properties within and outside BPAs[36].

Athukorala et al. (2019) also study BPAs in Australia, but for the state of Queensland (QND). The authors use a sample of 1028 properties distributed across four suburbs in the city of Brisbane: The Gap, Brookfield, Upper Kedron, and Chapel Hill. All properties sampled were sold between 1991-2011 and are located within 850 m of BPAs. The authors use the HPM to test for households' valuation of wildfire risk. Their findings suggest that prices of properties closest to the BPA are higher than those of properties further away. This is true within and across the four suburbs. The price discount associated with farness to BPAs is of 0.018, 0.052, 0.081, and 0.033 percent

[36] In contrast, we do look at the introduction of BPA maps (i.e., our research objective is different) and follow optimal procedures for the selection of the bandwidth. The latter is of high importance: a discretionary bandwidth, as that of Mo Koo & Liang (2022) is likely to generate estimates that suffer from either a high bias or variance, compromising the veracity of the results; whereas the optimal procedures that we follow guarantee an optimal bias-variance trade-off (see Methodology section below for more details).

for the suburbs of The Gap, Brookfield, Upper Kendron, and Chapel Hill, respectively. When regressing for the entire sample and introducing year dummies, the price discount is of 0.011%. Their findings suggest, that living closer to areas at risk of wildfires is positively valued, but the premium paid is very small. Athukorala et al. (2019) attribute this finding to the high amenity value of BPAs, which include forest reserves, bushlands, and a mixture of public and private green spaces. Nevertheless, the authors use a small sample size, raising doubts on selection bias. In addition, the authors do not use a clear identification strategy, but simply limit the sample to those properties within 850 m of BPAs, which – if we understand correctly – means that the sample is a mix of properties within and outside BPA boundaries, and, in any case, there is no distinction of properties within and outside BPAs in their identification strategy.

The literature review suggests that geographical discontinuities in regulations, environmental quality, and risk reduction effects create discontinuities in prices. Generally, areas affected by more stringent regulations, lower environmental quality, or higher exposure to risk have lower property prices than those on the other side of the geographical boundary – as long as individuals are aware of the geographical discontinuity of the good or regulation in question. One exception to this conclusion is Mo Koo & Liang (2022)'s paper on wildfire risk, as the authors find that property prices within BPAs are higher than outside BPAs, but the focus of the paper is the price update in BPA areas following a major fire. Another exception is Athukorala et al. (2019)'s paper which finds a negative link between property prices and distance to BPAs, but the authors do not distinguish between properties within and outside BPAs. Our study is, to the best of our knowledge, the first to analyse the information shock from the release of BPA maps on property prices.

2.3 METHODOLOGY

Given that we are working in a non-experimental setting where treatment and control groups can be clearly identified by the BPA boundary, and given that, in the neighbourhood of the boundary, observations are essentially equal in aspects different to the BPA designation, we are using a spatial RDD[37].

Treatment assignment is defined by the values of a 'running' variable X, i.e., a continuous variable that determines treatment depending on whether or not its value exceeds a cutoff point c. In the context of our study, X is a score based on d, the Euclidean distance between the property and the nearest edge of a designated BPA boundary line. We assume there are n properties, indexed by $i = 1, 2, \dots, n$ and each receives a score X_i. Property i is treated, i.e., belongs to a designated BPA, if and only if $X_i \geq c$, where $c = 0$. If property i is located at the boundary or within the boundary, X_i equals $+d$, and outside the boundary X_i equals $-d$:

$$X_i = \begin{cases} -d \; if \; X_i < c \\ +d \; if \; X_i \geq c \end{cases}$$

In an RD setting, a consistent average treatment effect (ATE) estimate may be obtained by focusing on observations around the cutoff point c, as long as unobservable factors are continuously related to the running variable X. In other words, the treatment

[37] This is very beneficial, as it produces estimates as good as those from a randomised experiment. Following a different approach, would require the use of control variables and further assumptions. A DD approach, for instance, would have yield a weaker identification strategy, as it would have required us to make assumptions for the identification of treatment and control groups, i.e., to arbitrarily define which properties are *near enough* to the boundary, potentially leading to selection bias, and to assume that, in absence of the BPA designation, property prices of treatment and control observations would move in tandem.

around the cutoff point may be as good as in a randomised experiment. This is true when economic agents do not precisely control assignment, and, therefore, the distribution of observed baseline covariates is continuous at the threshold (Lee & Lemieux, 2010). In the context of our study, we must ensure that households do not have the ability to precisely manipulate the assignment variable X, i.e., households cannot self-select or self-decline treatment by manipulating the distance between their property and BPV. We can test this by looking at the distribution of observed baseline characteristics, such as property size, number of bedrooms, number of bathrooms, etc., and corroborating that these have the same distribution and do not change discontinuously near the cutoff point c (Lee & Lemieux, 2010). But most importantly, we can critically think of the possibility of individuals manipulating the treatment assignment, i.e., can individuals actually interfere in the BPA designation process? If households are unable to precisely control X around the cutoff point, then the density of X is continuous, as in a randomised experiment.

Another factor that affects the estimation of the treatment effect is the level of compliance. When intention to treat is fully determined by the threshold rule but treatment is not, it is said that the RD setting is one of imperfect compliance - more commonly referred to and coined as fuzzy RDD by Trochim (1984). If, however, both intention to treat and treatment are fully determined by the threshold rule, the RD setting is not fuzzy, but sharp. In a sharp RD setting, the probability of treatment jumps from 0 to 1 when X crosses the cutoff point c. In other words, the probability of belonging to a designated BPA is equal to 0 when $X < 0$ and equal to 1 when $X > 0$. Given that BPA maps show a sharp boundary line, the RD setting of our study is not fuzzy, but sharp.

The following equations formalize the sharp RD setting of our study, based on Cattaneo et al. (2019). The outcome for each property, sale price Y_i, is conditional on receiving treatment. Therefore, each property has two potential outcomes, $Y_i(0)$ under control conditions and $Y_i(1)$ under treatment conditions, but only one observed outcome. If property i belongs to the treatment group, $Y_i(1)$ is observed and $Y_i(0)$ is the counterfactual unobserved outcome – and the opposite is true if otherwise:

$$Y_i = \begin{cases} Y_i(0) \; if \; X_i < c \\ Y_i(1) \; if \; X_i \geq c \end{cases}$$

An observation with score $X_i = c$ would be very similar to an observation with score $X_i = c - \varepsilon$, for a small and positive ε. The difference would lie in the treatment status. The local ATE on the treated in a sharp RD setting, τ_{SRD}, is the difference in conditional regression functions at c, and captures the average change in sale price for properties at the boundary of the BPA if these were to change from a control to treated status:

$$\tau_{SRD} \equiv \mathbb{E}[Y_i(1) - Y_i(0) | X_i = c]$$

This comparison between properties at opposite sides of the BPA boundary but with very similar scores rest on the assumption that the conditional regression functions are continuous at the cutoff point.

2.4 DATA

This paper looks at the introduction of maps identifying bush fire prone areas (BPAs) in WA, first released the 8th of December 2015. These are defined as "areas that have been identified as being subject, or likely to be subject, to bushfire attack" (DFES, 2021,

p. 2)[38], where bush fire is any unplanned vegetation fire, including grass, scrub or forest fire (AFAC, 2012, p. 5). The designation of BPAs is carried out by the Fire and Emergency Services (FES) Commissioner. All areas with a vegetation type classified as bushfire prone that is equal to or larger than one ha is directly identified as BPV[39]. Then, a buffer of 100 metres is applied to designated BPVs. The BPA is the conjunction of the BPV area and the 100-metre buffer. Overlapping buffers are merged to form a single BPA (DFES, 2021).

Furthermore, all new planning proposals in BPAs must be accompanied by i) a bushfire hazard level (BHL) assessment, ii) a bushfire attack level (BAL) contour map, if the lot layout is known, iii) the identification of potential bushfire hazards, and iv) demonstration that the planning proposal can meet with bushfire protection criteria in later stages (WAPC, 2015). Additionally, building work in designated BPAs must comply with the bush fire construction requirements of the Building Code of Australia (BCA), which apply with a four-month delay (Building and Energy, 2021); i.e., building work in BPAs designated on the 8th of December of 2015 must comply with bushfire construction requirements if the building permit was submitted on or after the 8th of April of 2016 (Building Commission, 2015).

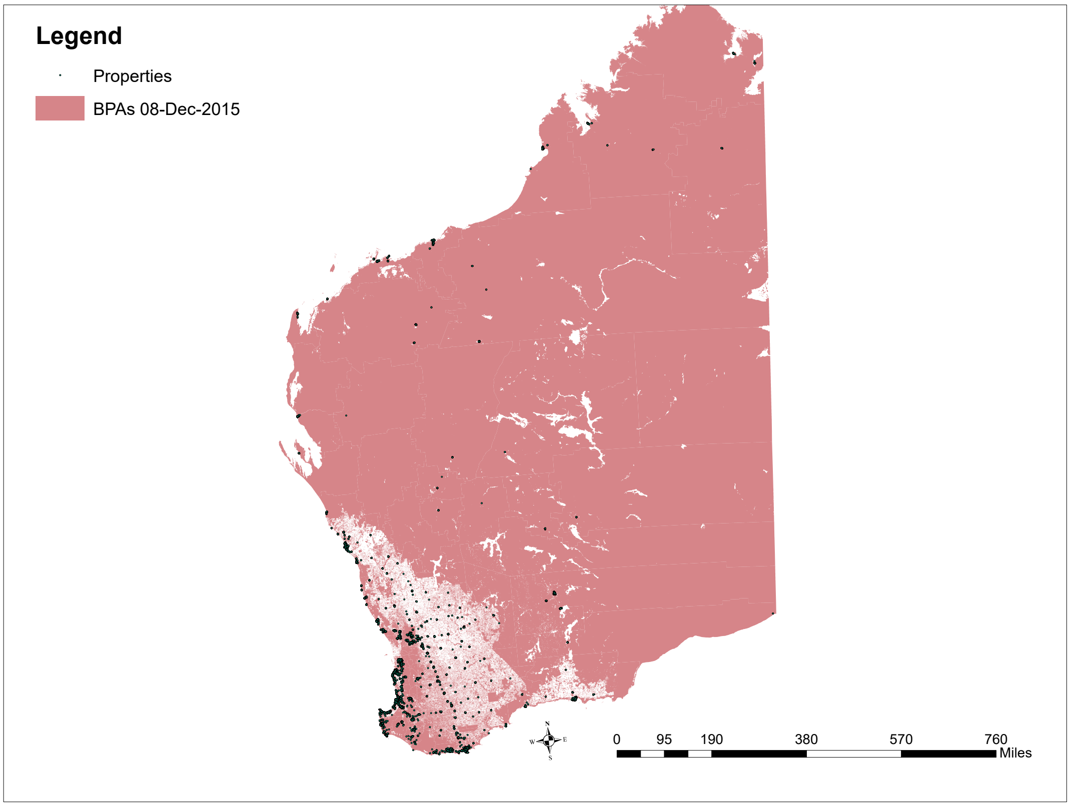
The BPA boundaries described above are obtained from BPA maps. Generally, BPA maps are released yearly on the 1st of June, before the start of the next Australian fiscal year (DFES, n.d.). However, the first edition of these maps was released on the 8th of

[38] The authors cite "Standards Australia 2019, Australian Standard Construction of buildings in bushfire prone areas AS 3959:2018, Fourth Edition incorporating Amendment No. 1, Standards Australia, Sydney, Australia p. 8" as source of this definition. This document is not publicly available.

[39] However, smaller areas may be identified as BPV depending on proximity to another BPV. For instance, BPVs may be as small as 0.25 ha as long as the proximity to a designated BPV is at most 100 metres. BPVs may also be smaller than 0.25 ha if located 20 metres or less from a designated BPV. Strips of vegetation that are at least 20 metres wide and at most 20 metres away from a designated BPV are also considered BPV, regardless of the strip length.

December of 2015, followed by subsequent editions, and, occasionally, updates and additional designations or removals. **Table 2.9.1** in the **Appendix** lists the datasets identifying BPAs in WA, according to the designation and release dates, along with the type of release. **Figure 2.1** shows the first edition of the BPA map released by the Government of Western Australia on the 8th of December of 2015, along with the residential properties sold between 2010-2019.

Figure 2.1: BPA map first edition and residential properties



Source: Own elaboration. Based on Government of Western Australia data and Australian Property Monitors data

To study the effect of the introduction of BPA maps, we use property market data for residential properties provided by Australian Property Monitors (APM). This dataset includes sale price, sale date, and a range of property characteristics, of which we only take the latitudes and longitudes. We also use several geographic information system (GIS) datasets provided by the Government of Western Australia. These are datasets on BPA boundaries, and neighbourhood and environmental attributes for the covariate-adjusted analysis. Using BPA boundaries, we construct the running variable ‘score’ by calculating the Euclidean distance between each property and the nearest boundary, and then we assign units to treatment and control groups by forcing the variable to take to a positive or negative value depending on whether these are inside or outside the BPA. The score variable takes a positive value if the property is inside the BPA at the moment of sale – therefore belonging to the treatment group – and a negative value if otherwise. For neighbourhood and environmental characteristics, we include distance to the nearest public beach, forested area and wetland, as well as to bus and rail public stops, schools, central Perth and urban land.

For the purposes of this study, we divide our data sample into two main groups: properties sold before the introduction of BPA maps (the pre-treatment period) and properties sold on or after the introduction of BPA maps (the treatment period). The pre-treatment period goes from the 1st of January 2010 to the 07th of December 2015, and the treatment period goes from the 8th of December 2015 to the 31st of December 2019. Additionally, we distinguish between two subgroups for each period: properties located within BPAs (the treatment group) and properties located outside BPAs (the control group). Patently, there is no real treatment group for the pre-treatment period. However, we create a placebo treatment group for the pre-treatment period for the purpose of undertaking validity tests of our RDD. **Table 2.4.1** below presents summary statistics for treatment and control groups on both periods. Our sample has a total of 89,895 observations, of which 57,434 belong to the pre-treatment period and 32,101 belong to the treatment period. Approximately 26 and 31 percent of observations belong to the treatment group for the pre and post treatment periods, respectively, while the remainder belong to the control group.

The running variable (score) takes negative values for the control group and positive values for the treatment group, and **Table 2.4.1** shows that properties can be as close as less than 1 metre away from the BPA boundary and as far as 17 kilometres away from the boundary. The maximum score in the treatment group for the treatment period is 2.7 times higher than the maximum score in the control group, suggesting that some BPAs in WA are extensive. Further details on other neighbourhood and environmental attributes are presented in **Table 2.4.1** below.

Table 2.4.1: Summary statistics for treatment and control groups and pre and post introduction of BPA maps

Pre-treatment period										
		outside BPA boundaries (control group)				within BPA boundaries (treatment group)				
Variable	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
log of sale price (AUD)	41,591	12.82	0.46	10.71	15.47	15,843	12.95	0.50	10.60	15.33
score (metres)	41,591	-457.90	721.80	-6,339.57	-0.003	15,843	305.08	1,101.32	0.0004	16,660.34
distance to nearest (km):										
bus station	41,591	21.19	75.42	0.01	734.72	15,843	27.80	54.98	0.01	733.34
bus station in CAT	41,591	317.32	399.82	24.37	2,208.39	15,843	280.17	332.24	18.41	2,202.75
train station	41,591	283.22	411.13	0.10	2,203.74	15,843	244.38	340.40	0.82	2,198.13
public school	41,591	1.00	1.50	0.00	36.04	15,843	2.33	5.79	0.00	311.03
Perth townsite	41,591	327.41	401.54	26.51	2,219.00	15,843	288.80	333.75	21.54	2,213.31
fire station	41,591	2.20	1.51	0.02	90.00	15,843	2.13	2.44	0.02	90.25
forested area	41,591	1.05	2.99	0.00	69.84	15,843	1.05	5.01	0.00	69.90
wetland	41,591	24.82	28.14	0.00	191.46	15,843	20.19	23.96	0.00	577.39
public beach	41,591	93.42	176.55	0.07	791.92	15,843	74.78	147.66	0.07	791.93
sandy coastline	41,591	47.93	99.61	0.02	598.97	15,843	41.52	83.09	0.05	554.00
urban land dummy	41,591	0.79	0.41	0.00	1.00	15,843	0.66	0.47	0.00	1.00
Treatment period										
		outside BPA boundaries (control group)				within BPA boundaries (treatment group)				
Variable	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
log of sale price (AUD)	22,298	12.75	0.42	11.00	15.36	9,803	12.95	0.47	11.25	15.62
score (metres)	22,298	-447.01	673.62	- 6,339.57	-0.020	9,803	522.94	1,670.12	0.03	17,326.68
distance to nearest (km):										
bus station	22,298	17.65	68.90	0.01	734.23	9,803	26.05	54.70	0.01	733.62
bus station in CAT	22,298	337.80	421.09	24.30	2,204.35	9,803	283.95	352.38	18.68	2,204.37
train station	22,298	303.21	433.05	0.18	2,199.73	9,803	247.87	359.83	0.17	2,199.74

public school	22,298	1.04	1.49	0.00	28.42	9,803	2.57	4.28	0.03	41.31
Perth townsite	22,298	348.40	423.36	23.58	2,214.92	9,803	292.96	354.33	21.66	2,214.95
fire station	22,298	2.28	1.45	0.02	16.86	9,803	2.16	1.65	0.04	20.15
forested area	22,298	1.22	3.42	0.00	69.79	9,803	0.99	4.34	0.00	69.65
wetland	22,298	24.22	28.45	0.02	188.70	9,803	16.83	19.56	0.00	191.15
public beach	22,298	99.48	191.54	0.09	791.79	9,803	62.92	142.26	0.11	791.96
sandy coastline	22,298	38.44	88.10	0.05	554.35	9,803	26.00	52.90	0.05	357.29
urban land dummy	22,298	0.78	0.42	0.00	1.00	9,803	0.63	0.48	0.00	1.00

[a] For the pre-treatment period, we assign BPA boundaries as of the 8th of December 2015 (first edition of BPA maps) to observations sold prior to this date.
Source: Own elaboration. Based on Data WA (Government of Western Australia data catalogue) and property market data obtained from APM.

2.5 RESULTS

To address our research question, we use the local polynomial approach for point estimation. We use a polynomial of first order ($p = 1$) for two reasons. First, because this choice is recommended by Cattaneo et al. (2019) because of the simplicity, precision, and stability of the local linear RD estimator. Second, because most of our observations are at small distance from the cutoff point[40], meaning that the unknown regression function is mostly determined by the values of observations in the neighbourhood of the threshold, and therefore, a higher order polynomial would do little in approximating the entire function more precisely. We chose a triangular kernel function along with the MSE optimal bandwidth selection method because this conjunction leads to an RD point estimate with optimal properties.

Table 2.5.1 below shows the estimated RD treatment effects. Results are obtained using observations of properties sold on or after the date of release of the first edition of BPA maps, i.e., on or after the 8th of December 2015. BPA boundaries used are those that correspond to the most recent edition available at the moment of sale, e.g., treatment status for a property sold on the 21st of May 2016 is defined by BPA boundaries of the second edition (see **Table 2.9.1** in the **Appendix**).

Our main results are those in column (1), under no covariate adjustment. No covariate adjustment is preferred for two reasons. First, including covariates may lead to an unreliable estimated RD treatment effect if covariates are imbalanced at the cutoff, or if treatment period values differ systematically from predetermined values. Second, covariate adjusted estimators can provide efficiency gains with shorter confidence intervals, but do not improve the identification strategy. Column (1) shows that, on

[40]Unlike most spatial discontinuities, the BPA polygons are numerous and of very different sizes and irregular shapes. For these reasons, many properties will be in close proximity to a BPA boundary.

average, properties located in designated BPAs experienced a price discount of 4.22%, statistically significant at the 1 percent level with both conventional and robust p-values. In columns (2) – (5) we adjust for pre-determined covariates that are independent of treatment status. In these columns, we always control for year FE, which are equal to all units regardless of treatment assignment status. Year FE control for year specific events that might have an impact on property sale prices, such as government elections. Column (3) controls for neighbourhood attributes, these are the Euclidean distances to the nearest bus stop, train stop, fire station, edge of the Perth townsite, and a dummy equal to unity if the property is on urban land. Column (4) controls for environmental attributes, including Euclidean distances to the nearest edge of a forested area, wetland, and sandy coastline, and to the nearest public beach, and column (5) includes controls for both neighbourhood and environmental attributes[41]. The conclusion remains the same in all columns: for the treatment period, properties under BPA designation experienced a price discount that ranges between 3.4–4.2% percent and this is significant at the 1 percent level under robust inference methods, and significant at least at the five percent level under conventional inference methods.

Bandwidth choice is highly influential on results due to the bias-variance trade-off. In **Table 2.5.1** below, we see that the bandwidth is small even under an MSE-optimal bandwidth selection method, suggesting that we have many observations at a close

[41] FE that account for spatial boundaries such as postcodes or suburbs and structural attributes are excluded because these may not be independent from treatment status. For instance, spatial boundaries might be (not causally) correlated to treatment status, e.g., postcodes or suburbs with a large proportion of BPV are more likely to be entirely, or in a large proportion, enclosed by BPA boundaries. Including spatial boundaries would violate the continuity assumption and invalidate the treatment effect estimation. Structural attributes might also not be independent of treatment status, as these might be influenced by bushfire construction requirements that apply within BPAs.

distance from the BPA boundary, which lowers the misspecification error without compromising the optimal bias-variance trade-off.

Table 2.5.1: RD Point Estimates

	(1)	(2)	(3)	(4)	(5)
RD estimate	-0.0422***	-0.0415***	-0.0338**	-0.0398***	-0.0353***
	(0.0142)	(0.0142)	(0.0134)	(0.0136)	(0.0132)
P>|z| Conventional	0.003	0.003	0.012	0.004	0.008
P>|z| Robust	0.001	0.001	0.005	0.002	0.003
Cutoff (c)	0	0	0	0	0
Covariates:					
Structural	No	No	No	No	No
Neighbourhood	No	No	Yes	No	Yes
Environmental	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Spatial FE	No	No	No	No	No
Effective obs. left	7,223	7,234	7,088	7,156	7,108
Effective obs. right	6,668	6,669	6,639	6,652	6,642
Bandwidth (h)	117.1	117.4	114.1	115.4	114.6

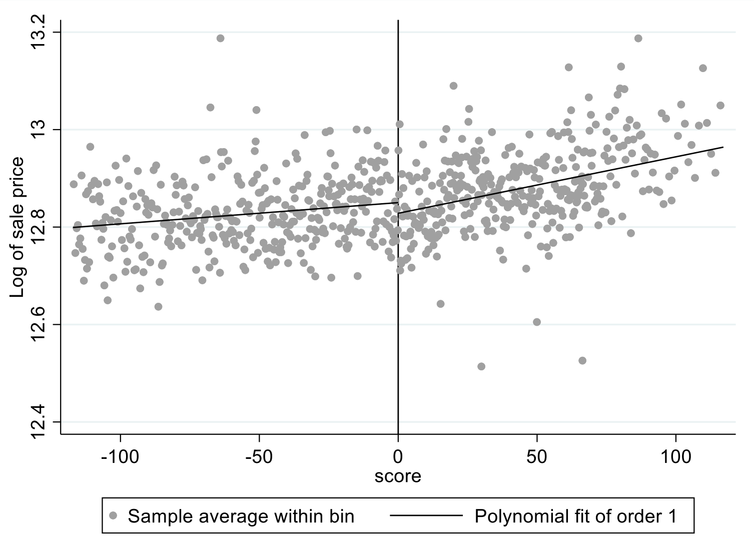
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The discontinuity of the outcome variable at the cutoff point can be visualized with an RD plot. **Figure 2.2** below provides a visual representation of our main findings in column (1) described above. The RD plot is constructed using the triangular kernel function along with the MSE optimal bandwidth of 117.1m, and a polynomial fit of order 1, as in the point estimation above. The number of bins is selected using the mimicking variance (MV) method to capture the variability of the data. Moreover, bins are quantile-spaced (QS) because these capture information on the density of the score, which is high around the cutoff point but increasingly lower toward the extremes[42]. We notice that the log of sale price is discontinuous at the BPA boundary line, with a downward jump for properties within the BPA, visually confirming our findings. Additionally, we see that, for properties within the BPA, sale price increases

[42] Evenly-spaced (ES) bins are discarded because the variance is high when observations are not uniformly distributed along the entire support of the score, as is our case.

with score. This is actually a confirmation of the high amenity value of vegetation. Given that the BPA encloses the area within 100 metres of a BPV, we can expect amenity values to be higher for properties further away from the boundary. In other words, as we approach and pass the BPA boundary, the sale price increases due to the high amenity value of vegetation, particularly for the first hundred metres within the boundary.

Figure 2.2: Regression discontinuity plot under QSMV bin selection method



2.6 DISCUSSION

Results from the previous section show that properties inside the BPA are sold at a discount[43]. In this section we explore the mechanism driving our results. We hypothesise three potential explanations for our results: i) it could be that the price differential was pre-determined by risk perception even before the introduction of BPA maps; if the discount is only observed during the treatment period, then ii) it might be that it is driven by stringent building regulations associated with BPA status;

[43] We note that it is possible that the impact of this lower property price on the wealth of the seller may be at least partially compensated by a lower tax paid for the sale transaction. Nonetheless, lower tax revenues imply fewer resources, including resources for public wildfire management.

or iii) it could be a pure information shock from the introduction of BPA maps that cause an update in risk perception. It is, of course, also possible that the discount is driven by a combination of all these three factors.

We implement the RD design for the pre-treatment period to identify if the RD treatment effect we get is a result of the capitalization of predetermined perceived wildfire risk instead of an effect from the introduction of BPA maps and consecutive designations. **Table 2.6.1** below presents two panels, Panel A for the pre-treatment period analysis, and Panel B for the treatment period. Results on Panel A are obtained using observations of units sold before the date of release of the first edition of BPA maps, i.e., before the 8th of December 2015. Results on Panel B, on the other hand, are the same as those presented in **Table 2.5.1** above. For Panel A, we use the BPA boundaries of the first edition. Column (A1) is the pre-treatment counterpart of column (B1) as both have the same specification and the only difference is the period of analysis. The same is true for columns (A2) and (B2). For the pre-treatment period, we get a negative but statistically insignificant effect, in contrast to the treatment period where the results are statistically significant. If we adjust for pre-determined covariates that are independent of treatment status, i.e., year FE, the conclusion remains the same: no significant impact is found for the pre-treatment period (see column A2). Overall, and regardless of covariate adjustment, results show that the BPA treatment effect is negative and statistically significant for the treatment period, but insignificant for the pre-treatment period – despite the larger sample of observations used in the estimation. We are therefore reassured that the discontinuity in the log of sale price is driven by the introduction of BPA maps and not by predetermined perceived wildfire risk. Moreover, we see that the bandwidth is similar for both pre and post treatment periods. This suggests that pre and post treatment estimates are comparable.

Table 2.6.1: RD point estimates for pre-treatment and treatment periods

	Panel A Pre-treatment period		Panel B Treatment period	
	(A1)	(A2)	(B1)	(B2)
RD estimate	-0.0152	-0.0152	-0.0422***	-0.0415***
	(0.0107)	(0.0107)	(0.0142)	(0.0142)
P>|z| Conventional	0.156	0.156	0.003	0.003
P>|z| Robust	0.110	0.110	0.001	0.001
Cutoff (c)	0	0	0	0
Covariates:	No	Year FE	No	Year FE
Effective obs. left	16,030	16,031	7,223	7,234
Effective obs. right	12,206	12,206	6,668	6,669
Bandwidth (h)	152.1	152.1	117.1	117.4

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

We now investigate if the BPA effect is driven by additional regulatory costs borne by households of existing buildings, i.e., driven by the cost of compliance with bushfire construction requirements as outlined in the BCA. We call this the ‘regulation effect’ and to estimate it we compare the RD point estimates obtained using two samples. The first sample contains observations of repeat-sales properties that were re-sold after the introduction of BPA maps on the 8th of December of 2015. We can safely assume that any property in this sample is not new, because it has been sold before the introduction of BPA maps. However, it might have undergone building work and we are not able to filter this. The second sample contains observations of unique-sales properties that were sold after the more stringent building regulations are in place, on the 8th of April of 2016. We can make the assumption that at least some of these properties were affected by the more stringent planning and building regulations. Results in **Table 2.6.2** show that the RD estimate is statistically significant for both samples (see Panels A and B) regardless of covariate adjustment choice (see columns 1 and 2 in both Panels). Furthermore, we can see that confidence intervals of RD estimates intersect (see ‘C.I. Robust’ for A1 and B1, and for A2 and B2), suggesting that RD estimates from both samples are not statistically different from each other, i.e., that the regulation effect is not statistically significant. Hence, we suspect that the BPA effect is not driven by the regulation effect, but rather from a pure information shock.

Table 2.6.2: RD point estimates for the 'regulation effect'

Sample	Panel A Repeat-sales properties re-sold after BPA map introduction		Panel B Unique-sales properties sold after building regulations	
	(A1)	(A2)	(B1)	(B2)
RD estimate	-0.04222** (0.02488)	-0.04101* (0.02488)	-0.03122*** (0.01258)	-0.03102*** (0.01257)
P>|z| Conventional	0.090	0.099	0.013	0.014
P>|z| Robust	0.048	0.053	0.006	0.006
C.I. Robust	[-0.1034, -0.0005]	[-0.1022, +0.0007]	[-0.0598, -0.0100]	[-0.0596, -0.0100]
Cutoff (c)	0	0	0	0
Covariates	No	Year FE	No	Year FE
Effective obs. left	2,207	2,210	8,291	8,294
Effective obs. right	1,408	1,408	5,482	5,482
Bandwidth (h)	193.0	193.6	261.2	261.6

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

The results presented in this section suggest that the treatment discount we observe for properties located inside the BPA is not driven by pre-determined risk perception, nor it is the result of more stringent planning and building regulations associated with BPA designation. We therefore conclude that our results are most likely driven by an information update related to the BPA designation of the properties. We argue that the introduction of BPA maps served as an information shock on wildfire risk for three reasons. First, the maps are open access and specially designed for people to search their address and learn if their home is within a BPA or not. Second, BPA designation sharply divides areas *prone* to bushfires from those otherwise. Third, prior to these maps, Western Australians lacked an official and community-oriented source of information on land's wildfire risk. Our results provide insights into society's WTP to avoid wildfire risk.

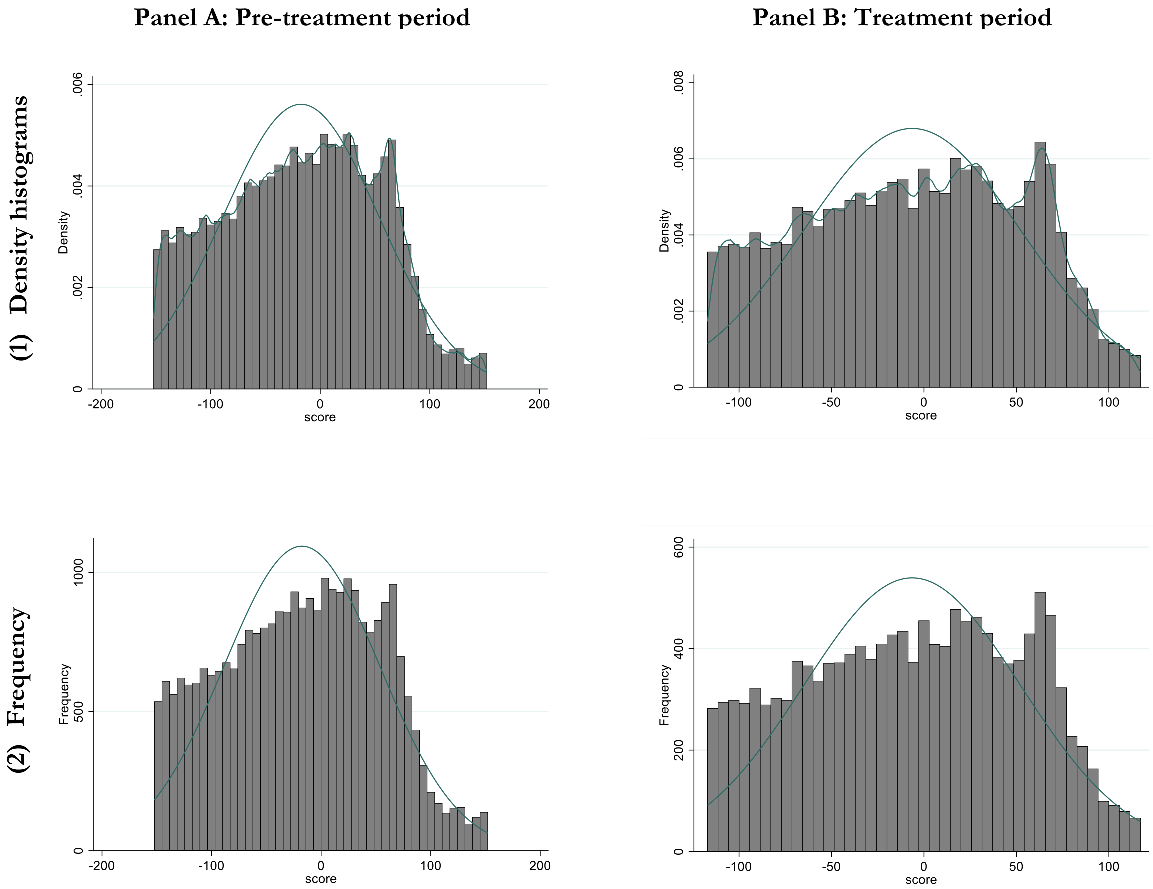
2.7 VALIDATION TESTS

The validity of the RD design can be corroborated with qualitative information (Cattaneo, et al., 2019). For example, we may be worried about precise manipulation of treatment if households are aware of the cutoff rule, and it would be beneficial to know if households can appeal the designation of BPAs, and if so, how often they do. However, households may be able to manipulate assignment informally, or there might be no qualitative information available at all. In this section, we test the validity of the RDD using empirical evidence and implementing different validation tests proposed by authors such as Cattaneo et al. (2019).

Our first validation test examines the number of observations in the local neighbourhood of the cutoff to rule out precise manipulation of treatment assignment, i.e., if there is a large difference between the number of observations just below and just above the cutoff value, we cannot rule out that households precisely manipulate treatment assignment either by moving from BPAs to non-BPAs or by influencing the BPA designation decision. Panels A and B in **Figure 2.3** below show the histograms for the pre and post-treatment periods, respectively, using the same MSE-optimal bandwidth as in our main results, i.e., 152.13 meters for the pre-treatment period, and 117.1 metres for the treatment period. Moreover, we present two types of histograms: row (1) presents density histograms with normal and triangular kernel density estimates, and row (2) presents frequency histograms with normal density estimates. We can see that the number of observations decreases continuously when the score is approximately above 60 for both the pre and post treatment periods. This indicates there is some level of sorting within BPAs even before these were designated. However, the number of observations or density of the score look fairly similar for the cutoff value.

Using a local polynomial density estimation under a polynomial fit of order 2 (default option) and imposing the MSE-optimal bandwidth of our main results, we find no evidence of precise manipulation of treatment assignment or sorting around the cutoff for any period. **Table 2.7.1** below presents the local polynomial density estimations

Figure 2.3: Validation test - Histogram of the score around the cut-off



of the running variable (score) for the pre-treatment period (Panel A) and the treatment period (Panel B) using the MSE-optimal bandwidth from our main results, which we input manually, and a polynomial fit of order 2, for the pre and post-treatment periods, respectively. Under this specification, we do not reject the null hypothesis H0 of continuity of the density functions for control and treatment units at the cutoff (no precise manipulation of the density at the cutoff), i.e., we do not find evidence of a discontinuity of the score around the cutoff value. **Figure 2.4** in the appendix shows the manipulation testing plots for results in Panel A and B of **Table 2.7.1** below. Here, we see that the confidence intervals for the local polynomial density estimations for the treatment and control groups overlap, which explains why we do not reject the null hypothesis of continuity of the score around the cutoff.

Table 2.7.1: Validation test - Manipulation test using local polynomial density estimation

	Panel A Pre-treatment period	Panel B Treatment period
Bandwidth selection method	Manual	Manual
Bandwidth (h) left	152.13	117.1
Bandwidth (h) right	152.13	117.1
Polynomial order (p)	2	2
T-statistic	-1.4698	-1.5688
P>|T|	0.142	0.117
Reject H_0	No	No
Cutoff (c)	0	0
Observations:		
effective (left)	16,030	7,223
effective (right)	12,206	6,668

Our second validation test is known as the 'donut-hole approach'. For this test we exclude observations near the cutoff point to check for sensitivity to observations near the cutoff. If manipulation has occurred, it has very likely occurred for units near the cutoff point. If manipulation has not occurred, it is likely that excluding observations very near the cutoff point does not change the estimated treatment effect. We implement the donut-hole approach by excluding observations within 1, 5, 10, and 20 metres on either side of the boundary (see **Table 2.7.2** below). The RD treatment effect of our main results continues to be robust when the donut-hole is 1, 5 or 10 metres wide, i.e., we get a negative RD estimate close to 4% and statistically significant at least at the five percent level. However, as we exclude a larger number of observations near the cutoff and as the MSE-optimal bandwidth becomes larger, the

RD estimate becomes unreliable, i.e., changes sign and/or becomes statistically insignificant. This is expected because a local polynomial point estimation requires of observations near the boundary. A donut-hole of 20 metres or more removes a significant number of observations from our dataset (e.g., removes 10 percent for a donut-hole of 20 metres and these removed observations represent 22 percent of the observations within a bandwidth of 116 metres). In other words, a donut-hole of 20 metres and beyond significantly distorts the relevance of the sample selected for the analysis. Overall, this validation test supports the assumption of no precise manipulation of treatment assignment, suggesting that the density of the score is continuous and our results are as good as in a randomised experiment.

Table 2.7.2: Validation test, donut-hole approach

	(1)	(2)	(3)	(4)
Donut hole: |score| ≤	1m	5m	10m	20m
RD estimate	-0.0416***	-0.0501***	-0.0406**	-0.0086
	(0.0146)	(0.0165)	(0.0183)	(0.0226)
95% C.I Robust	[-0.078; -0.018]	[-0.091; -0.023]	[-0.086; -0.011]	[-0.065; 0.027]
P>|z| Conventional	0.005	0.003	0.027	0.702
P>|z| Robust	0.002	0.001	0.011	0.423
Cutoff (c)	0	0	0	0
Covariates	No	No	No	No
Effective obs. left	7,086	6,494	6,058	5,736
Effective obs. right	6,549	6,166	5,799	5,122
Bandwidth (h)	115.4	108.8	107.5	116

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

Our final validation test consists of using a different bandwidth to check for the sensitivity to bandwidth choice. Since results would be unreliable with a bandwidth far from the MSE-optimal choice, we try with a bandwidth 10, 20 and 50 percent higher than the MSE-optimal bandwidth of our main results ($h_{MSE} = 117.1$), i.e., we implement the RDD by manually selecting bandwidths of 128.8, 140.5, and 175.7 metres. Our results remain robust under these bandwidth choices, i.e., the RD estimate continues to be negative, close to 4%, and highly statistically significant – see columns (1) to (3) in **Table 2.7.3** below. On the other hand, if the bandwidth choice is 5 times larger than the MSE-optimal (117.1 x 5 = 585.5), the disparity between the effective number of observations to the left and right of the cutoff point is high and the RD estimate changes sign. Therefore, results on column (4) are unreliable. The results from this test suggest that the robustness of our RD estimate is not threatened by observations immediately further (approx. 60 m) of the neighbourhood endpoint.

Table 2.7.3: Validation test - Sensitivity to bandwidth choice

	(1)	(2)	(3)	(4)
Bandwidth (h):	128.8	140.5	175.7	585.5
RD estimate	-0.0419***	-0.0420***	-0.0413***	0.0174**
	(0.0137)	(0.0133)	(0.0122)	(0.00811)
P>|z| Conventional	0.002	0.002	0.001	0.032
P>|z| Robust	0.025	0.025	0.013	0.000
Cutoff (c)	0	0	0	0
Covariates	No	No	No	No
Effective obs. left	7,795	8,318	9,738	17,368
Effective obs. right	6,801	6,940	7,277	8,666

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

Overall, the outcomes of the validation tests detailed above suggest that our RD design is valid, i.e., no statistical evidence of precise manipulation of treatment assignment and robustness of the RD estimate to bandwidth choice. Furthermore, the level of transparency in the BPA designation is high because BPA maps are public and open access, making it difficult to manipulate treatment assignment. Additionally, correspondence with the DFES confirms that appeals to designations are rare and updates to the map generally capture changes in vegetation cover due to clearing and development. Thus, there is no anecdotal or statistical evidence of precise manipulation of treatment assignment, supporting the validity of our RD design and estimates.

2.8 CONCLUSIONS

In this paper, we study the implicit value of safety, revealed by an information shock in the housing market: the introduction of wildfire risk maps. These maps create a sharp geographic discontinuity that divides properties into two groups. The first group contains properties within BPAs, our treatment group. The second, contains properties outside BPAs, our control group. Aided by an RDD set-up, our treatment and control groups are formed from observations of the first and second groups, respectively, at a neighbouring distance from the boundary line. This permits us to estimate a local average treatment effect (LATE) that is as good as in a randomised experiment. Our findings suggest that preferences for safety are heightened when BPA maps are released into the market: properties within BPAs are sold at a price discount of 4.2% compared to those within non-BPAs. Moreover, our findings indicate that the price differential is not triggered by pre-determined risk perceptions nor by stringent regulations. Therefore, we find that the release of wildfire risk maps triggers an information shock that translates into an increase for safety preferences.

Our findings suggest that society might initially adapt to climate change by assigning a higher value to safety, a good that is predicted to become scarcer as the likelihood and intensity of uncontrollable wildfires increase. On one hand, the publication of user friendly and open access wildfire risk maps, such as those of WA, has the potential to reduce management, suppression, and recovery costs by increasing wildfire risk awareness and discouraging housing in the riskiest areas. On the other hand, it potentially increases risk exposure of lower income households, exacerbating social inequality around wildfire risk that is already documented, e.g., Masri et al. (2021), Holloway & Rubin (2022), Burke et al. (2022) and Anderson et al. (2023). Policy makers need to be aware of this change in preferences in order to put forward adequate adaptation measures that protect society's wellbeing, wealth, and promotes social justice. In other words, the introduction of BPA maps tries to address market failure from lack of information, but can have unintended consequences with distributional concerns by affecting the locational choices of low income households across the BPA boundary.

However, our findings suggest that the introduction of BPA maps might have positive impacts on welfare. First, because the information shock may well be closing an information gap regarding wildfire risk. This is particularly true if we believe that households in wildfire prone areas are currently underestimating wildfire risk[44]. Second, because the regulation shock for the compliance with bushfire requirements for planning and building activities may reduce wildfire risk; effectively translating into positive externalities for neighbouring properties and reducing the expected costs of fire suppression for the state[45].

[44] We believe substantiating such a claim would require the use of survey data from WA, where the focus of questionnaires is on contrasting subjective risk perception against some objective measure of wildfire risk.

[45] Taking the Waroona Fire of 2016 as an example, the town of Yarloop was almost entirely destroyed because the fire spread from one building to another through ember attack, facilitated by the strong presence of timber in properties (Government of Western Australia, 2016) – see section 1.4 in **CHAPTER 1** above for more details on the Waroona Fire. The larger the number of dwellings affected, the higher we can expect fire suppression costs to be.

2.9 APPENDIX

Table 2.9.1: BPA designations

No.	Dataset	Date of designation	Date of release	Release type
1	Bush Fire Prone Areas 2015 (OBRM-002)	08-12-2015	08-12-2015	First edition
2	Bush Fire Prone Areas 2016 (OBRM-004)	21-05-2016	01-06-2016	Second edition
3	Bush Fire Prone Areas 2017 (OBRM-008)	01-06-2017	01-06-2017	Third edition
4	Bush Fire Prone Areas designated on 12-07-2017 (OBRM-010)	12-07-2017	12-07-2017	Additional designation
5	Bush Fire Prone Areas 2018 (OBRM-011)	01-06-2018	01-06-2018	Fourth Edition
6	Bush Fire Prone Areas 2019 (OBRM-013)	01-06-2019	01-06-2019	Fifth Edition
7	Bush Fire Prone Areas 2019 No2 (OBRM-015)	31-07-2019	31-07-2019	Update to Fifth Edition
8	Bush Fire Prone Areas 2019 No3 (OBRM-017)	28-09-2019	28-09-2019	Update to Fifth Edition

Source: Own elaboration. Based on Data WA, the Government of Western Australia data catalogue.
Note: All datasets, except for dataset #4, identify BPAs for the whole of WA as designated on the date of release. Dataset #4, on the other hand, rectifies for anomalies on the third edition, and therefore only identifies additional areas. For a complete identification of BPAs between the 12th of July of 2017 and the 1st of June of 2018, datasets #3 and #4 must be used in conjunction.

Figure 2.4: Manipulation testing plots

Table 2.7.1, Panel A

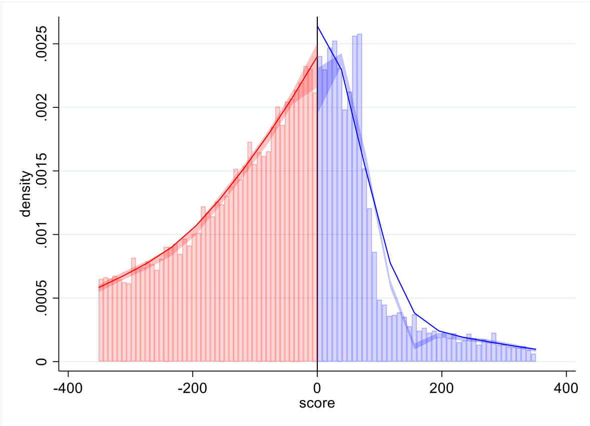
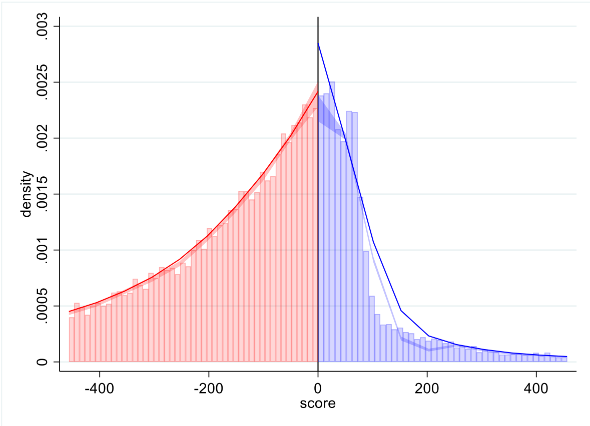


Table 2.7.1, Panel B



CHAPTER 3 FOREST MANAGEMENT PRACTICES AND SAFETY PREFERENCES: DO HOUSEHOLDS WELCOME PRESCRIBED BURNING?

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ABSTRACT

In this paper, we use the hedonic price method to identify preferences for prescribed fires in Western Australia, a region with a strong history in the use of this forest management practice, amid a polarized view on its moral and scientific value. Using property fixed effects to account for unobservable time-constant attributes, and controlling for wildfires, we find a positive preference for prescribed fires. Moreover, we find stronger results for more recent fires, presumably due to the decreasing nature of risk reduction effects over time. Our findings also suggest that households' risk perceptions are more susceptible to frequency of fires, rather than consequence – given that our results are stronger when we use number of fires as exposure indicator instead of area burnt. Capitalisation of prescribed fires is moreover much higher for properties with no wildfire experience. Additionally, our findings suggest that time-constant unobservable attributes significantly explain safety preferences for prescribed burning, making the use of property fixed effects essential.

3.1 INTRODUCTION

In February 2022, the United Nations environment programme (UNEP) published a report dedicated to wildfire risk urging governments to revisit their management approach to wildfires. The report highlights the fact that wildfires are becoming more intense and frequent, with devastating consequences to communities, ecosystems, and biodiversity; and that climate and land-use change are contributing to this situation. The UNEP report recommends that governments spend more on risk reduction, rather than on fire suppression, given that risk reduction is more cost-effective in the long term (UNEP, 2022).

In Western Australia (WA), prescribed burning, i.e., the action of planning a fire and applying it to a predetermined area (DBCA, 2023), has been used extensively as a state fire management tool since the 1960s (McCaw, et al., 2003) – although it was a practice undertaken by indigenous Australians long before colonisation of the southwest in 1828 (Abbott, 2003). Nevertheless, the proportion of forests in the southwest of WA treated by prescribed fires has been declining since the 1970s at the same time as the proportion burnt by wildfires has been increasing since late 1980s. Large wildfires, i.e., greater than 20 thousand hectares (ha), are no longer rare since 1997, and prescribed burning targets have been rarely achieved since 2000 (Burrows & McCaw, 2013). Indeed, the practice has been limited by changes in climate that make it more risky (Keelty, 2012), discontent of communities and industries from smoke emissions (Reisen, et al., 2011), and by a more populated wildland urban interface (WUI) and land-use change (e.g., fragmented forests due to bauxite mining and timber harvesting industries), which generate burning constraints (Burrows & McCaw, 2013). Public concerns around biodiversity loss are also at the heart of the discontent with prescribed burning and generate strong polarisation. News articles in the media clearly expose the public's concerns.

For instance, in February 2023, David Wake, a resident from the City of Wanneroo made a plea to end prescribed burning in urban bushlands and replace it with weed management and community surveillance. His concerns were about wildlife not being able to retreat or recolonise burnt areas, given that these habitats are surrounded by urban developments. (Tan, 2023). A similar concern was raised in 2021, in Perup, an area home to the numbat, a small marsupial classified as endangered since 2014. Conservationists accused the Department for Biodiversity, Conservation, and Attractions (DBCA) of destroying its habitat. Following this accusation, the DBCA made clear that the fire strategy enabled numbats to access refuge areas and that healthy numbats were seen after the fire (Bennett & Edwards, 2021).

Some scientists are also taking an active part of this opposition due to biodiversity concerns. For example, in October 2022, a group of natural scientists from the state organised a volunteering activity for taking samples and photographs of plants and insects in a tingle forest in the south coast of WA before a prescribed burn to be implemented as part of the 2022/23 burning programme. They were concerned about the potential loss of native biodiversity. These efforts were made despite the DBCA clearly stating their intention to conduct a detailed flora and fauna survey of the treatment area before ignition (Bennett, 2022), exhibiting a strong distrust for the authority.

Furthermore, an independent group of scientists formed The Leeuwin Group (TLG) with the purpose of providing scientific advice on environmental matters (TLG, 2023). Joanna Young, a member of TLG, expressed concerns that prescribed fires threaten the composition of vegetation types when undertaken in forests, as is the case in the Walpole Wilderness area. She believes human assets and political are "put above the survival of a unique landscape" and criticizes the DBCA for setting more prescribed fires in the wild instead of around towns (Pepper, 2021).

Another member of the TLG, Stepehen Hopper, accused the DBCA of not mapping peat swamps accurately and urges the authority to implement smaller scale fires to protect biodiversity values. His declarations come after a prescribed fire in 2022 in North Walpole escaped and doubled its size to 25 thousand ha and threatened peat marshes and granite outcrops (Le May, 2022). Truth be told, in 2019, a prescribed fire destroyed a 5-thousand-year-old peat swamp, likely along abundant endemic flora and fauna species (Pepper, 2021). On both occasions, the DBCA defended the prescribed burning practice, indicating that benefits of preventing tragedies outweigh the costs and risks (Le May, 2022), and that they do consider these special ecosystems in their strategy (Pepper, 2021).

Others oppose to prescribed burning due to the smoke haze produced by the fire. For example, prescribed fires around Perth in April 2022 were met with public health experts raising alarms concerning the negative impacts of smoke haze, such as breathing difficulties, headaches, and high blood pressure. Indeed, listeners to ABC Radio Perth shared that they experienced some of these symptoms, and that smoke haze made it impossible to enjoy favourable weather (Bell & Wynne, 2022). Smoke haze from prescribed burns may also pose important visibility problems, such as those occurring in Perth in May 2022, reducing visibility on roads (Steger, 2022).

Some others distrust the effectiveness of prescribed burning in reducing the risk of wildfires. Indeed, some even go as far as claiming that prescribed burning *increases* the risk of wildfires. Associate Professor Phil Zylstra from Curtin University, Perth, co-published a controversial paper claiming that prescribed burning makes forests more prone to fire, in comparison with older vegetation areas. Research findings suggest that long unburnt forests in WA are three times less likely to catch fire than in recently prescribed burnt areas, even when fuel in recently prescribed burnt areas is less than 6 years old and even under the worst climatic conditions. Zylstra et al. (2022) suggest that areas recently burnt by prescribed fires face dense forest regrowth soon after, whereas long unburnt areas had self-thinned after a fire due to competition of resources among regrowth. Therefore, Zylstra suggests that prescribed burning should only be practiced near assets and homes, whereas fires in remote areas should be suppressed[46]. This is a proposition that the DBCA does not support, as the paper's findings contradicts peer-reviewed research and operational evidence from over 60 years that confirms that reducing combustible fuel through low intensity prescribed burning leads to lower risk of fire (de Kruijff, 2022).

Today, the future of prescribed burning in WA is uncertain. Just earlier this year, in June 2023, Australian Broadcasting Corporation (ABC) News reported that a group of conservationists had written a report and presented it to the Government of WA, in an attempt to get an independent review of the state's prescribed burning practices (Shine, 2023). However, the call was rejected by a WA parliamentary committee; a decision most welcomed by those who support the continuation of the practice as it is. For instance, John Clarke, the Chair of Bushfire Front (BFF), an organisation of 'practical bushfire specialists' that advocate for 'better' fire management (BFF, n.d.),

[46] Findings from Florec et al. (2020) would somewhat agree with Zylstra's proposition. Florec et al. (2020) undertake a long-term cost-benefit analysis of implementing prescribed burns in the southwest of WA for two hypothetical scenarios: the first is one where only landscape is treated, and the second is one where only the WUI is treated. They find that treatments on the WUI are more effective in reducing damage. However, treatments on the WUI are also much more expensive and not cost-efficient.

described the decision as a “triumph of science, common sense and logic over what I would refer to as unfounded ideologies” (Bold & Bennett, 2023).

Debates on prescribed burning are not only occurring in WA. At the national level, the revival of debates about prescribed burning in Australia has been linked to the 2019/20 *Black Summer* bushfires (BBC News, 2020), which were perceived as “different” and “terrifying” (Bowers & Mason, 2020). Opinions on this matter have been voiced at a high level, with a former member of parliament of the National Party of Australia and a former Prime Minister, Barnaby Joyce and Scott Morrison, respectively, showing strong support for prescribed burning and urging an increase in the frequency of its application. On the other hand, the Australian Greens, a political party in Australia, has been accused of opposing to prescribed burning, despite declaring they support the practice under expert guidance (BBC News, 2020).

Amid the divergent opinions of scientists, field practitioners, and the general public, the preferences of households directly affected by prescribed fires have not been sufficiently studied. This is the purpose of this study. In particular, we study changes in property prices associated with past exposure to prescribed fires. Importantly, we control for wildfire exposure.

Using the hedonic price method (HPM) and high-quality geographic information system (GIS) data, we find evidence of a positive preference for prescribed fires, especially for households with recent exposure. This finding suggests that households are well aware of the risk reduction effects from prescribed burning – which dominate over any disamenity impact - and that households take into account the decreasing nature of these effects over time as vegetation grows back. We also find suggestive evidence of strong substitution of risk reduction effects between prescribed and wildfires.

The next section presents an overview of the economic literature on prescribed burning, followed by a glimpse into the prescribed burning strategy in WA. Section 3.4 presents our methodology. Section 3.5 presents a description of our data. Section 3.6 presents our results. Section 3.7 presents a discussion where we explore the impact of wildfire disasters and alternative methodologies. Finally, we present our conclusions.

3.2 LITERATURE REVIEW

The literature review search was focused on economic literature on preferences for prescribed burning. The review was conducted through three main sources: the American Economic Association (AEA) database EconLit, the University of Birmingham's library catalogue search engine FindIt@Bham, and the Bushfire & Natural Hazard Cooperative Research Centre (BNHCRC) website using keywords and, when available, Boolean phrases. Additionally, we did a Google search for news articles on prescribed burning in WA. When relevant, we incorporated journal articles cited in the search results obtained. **Table 3.2.1** below describes the terms, filters and number of results for each search source, along with the last date in which the search was conducted. After reviewing abstracts, relevant results were selected.

Table 3.2.1 Literature review search description

Search source	Search terms	Additional filters	Number of results	Date of search
EconLit	"prescribed burning" OR "hazard reduction burning" OR "controlled burning" OR "prescribed burn" OR "hazard reduction burn" OR "controlled burn" OR "prescribed fire" OR "fuel treatment"	Apply related words; Apply equivalent subjects	68	21/06/2023

EconLit	("prescribed burning" OR "prescribed fire" OR "prescribed burn" OR "hazard reduction burning" OR "hazard reduction burn" OR "fuel treatment") AND ("hedonic price" OR "hedonic pricing" OR "housing market")	Apply related words; Apply equivalent subjects	0	21/06/2023
FindIt@Bham	Any field contains "prescribed burning" OR "hazard reduction burning" OR "controlled burning" OR “prescribed burn" OR "hazard reduction burn" OR "controlled burn" OR "prescribed fire" OR "fuel treatment" AND Any field contains "hedonic price" OR "hedonic pricing" OR "housing market"	Search for "Everywhere", Search Scope "Everything", Material Type "All Items", Language "Any Language"	2	21/06/2023
BNHCRC	“prescribed burning”	Not applicable	4	21/06/2023
Google	prescribed burning Western Australia	News	16	21/06/2023

Several studies look merely at the impacts of wildfires on property prices (e.g., Athukorala et al. (2016) for Australia, and Loomis (2004), Mueller et al. (2009), McCoy and Walsh (2018), etc., for the United States of America (US)). There appears to be an important gap, however, on the impacts of wildfire management on property prices. Indeed, whilst our literature review search reveals that, although there is ample research done over the period of late 1990s-2010 on preferences for fuel treatment, *none* of these examine the impact of fuel treatments on property prices. To the best of our knowledge, it is only the study by Hjerpe et al. (2016) that quantifies this impact, albeit indirectly. The authors study household preferences for forest density, an environmental attribute that is associated with wildfire risk. The following paragraphs describe this literature, starting with Hjerpe et al. (2016), and following with a review of studies using contingent valuation (CV), a stated preference technique, for the valuation of fuel treatments, which are presented on surveys as means to protect homes or as a means to enhance forest amenities.

Hjerpe et al. (2016) examine preferences for forest density in the housing market in the WUI using sale prices and attributes for houses sold during the period of 2011 – 2014 from four counties in the western area of the United States of America (US): Coconino in Arizona, Deschutes in Oregon, El Dorado in California, and Missoula in Montana. All houses, along with WUI areas, lakes, reservoirs, rivers, and fire stations are geolocated and authors were able to identify houses within the WUI and the distances to environmental attributes and fire stations. Forest density was calculated by identifying tree presence at a resolution of one m^2, for radii of 100 and 500 metres around each house parcel's centroid. The total number of observations in the sample is just above 400. The authors implement the HPM using spatial error and lag models to account for spatial dependence across error terms and sale prices, respectively. The results suggest a preference for low forest density in the immediate surroundings of houses in the WUI, with an opposing preference when considering less immediate surroundings. Moving from low to high forest density for the 100-metre radius entailed a price discount of approximately seven percent, whilst moving from a low to a high forest density for the 500-metre radius entailed a price mark-up of approximately nine percent. The most important suggestion, however, is that the housing market may be capitalising wildfire risk, which is implicit in forest density, along with amenity values and benefits for cooling effects. Moreover, the authors note that the preference for high forest density at the 500-metre buffer level - under a context of high wildfire risk in the area and a rapid expansion of the WUI house development – indicate market failure that could arise from two sources. First, from incomplete information, and consequently, low awareness of wildfire risk. And second, from publicly funded fire management services, which effectively serve as government subsidies, and generate free-rider effects on households choosing to live in fire-prone areas but not fully assuming the costs.

Turning away from market revealed preferences, a large group of studies rely on contingent valuation for valuing fuel treatment services. A first subgroup studies households' valuations for fuel treatment itself, whilst a second subgroup looks more closely at the biodiversity and recreational gains from fire prevention programs. From the first subgroup, Nahuelhual-Munoz, et al. (2004) and Loomis et al. (2005)'s studies look at preferences for fuel treatments across different states of the US; whereas Loomis, et al. (2004), Gonzalez-Caban et al. (2007), and Loomis et al. (2009) consider differential preferences across diverse communities or ethnic groups, also in the US. By contrast, Loureiro et al. (2004) and Kaval et al. (2007) focus on a single state.

Nahuelhual-Munoz, et al. (2004) describe prescribed burning as a public program that generates a public good and a public bad. The public good is the reduction in the risk of catastrophic wildfires, and it is non-rejectable. The public bad is smoke emissions. Therefore, prescribed burning programs might generate positive and negative willingness to pay (WTP), depending on the individual's valuation of the public good and bad. The authors estimate the WTP of households in California and Montana, US using survey data from July 2001 – May 2002 and present a set of models with different levels of ability to accommodate heterogeneous preferences: binary logit, simple spike, and parametric extended spike models[47]. The survey design involved first

[47] The latter are models which - in contrast to simple spike models - allow to address heterogeneous preferences by allowing different portions of the population to value the program of interest positively, negatively, or indifferently (value equal to zero). Responses from households who value the program negatively or indifferently are therefore not regarded as "protest", but instead accounted as authentic

providing a booklet with information on the benefits of prescribed burning (acres burnt reduced by 25 % and lower house loss), followed by a screening question on whether they would take the program at no cost; if they answered "yes", then they were presented with bids for costs ranging from 15 to 480 United States dollars (USD), and if they answered "no", respondents were presented with bids for payments to accept compensation from the state (benefits) ranging from 10 to 470 USD.

The results show that WTP estimates from the binary logit model are much higher than the most flexible version of the parametric extended spike model (560 vs. 104 USD). This is explained by the fact that the binary logit does not account for negative or indifferent values in responses, i.e., all valuations of the prescribed burning program equal to zero or with negative values are disregarded and considered as "protest" responses. The parametric extended spike models, on the other hand, do account for zero and negative valuations as authentic values. Indeed, WTP estimates for positive and negative responses using the most flexible extended spike model are 331 and -226 USD, resulting in a net WTP of 104 USD – which provides a better picture of the welfare gains and losses than the binary logit does. Nahuelhual-Munoz, et al. (2004)'s study therefore concludes that binary logit models overestimate WTP, and that prescribed burning programs may generate large welfare losses that should be accounted for even if the proportion of respondents with negative WTP estimations is low - as those of California and Montana (less than 1/5 of respondents). Their conclusions are supported by Loureiro, et al. (2004), who compare the binary logit model with the double-bounded logit model and the Turnbull estimator using survey

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zero or negative values. The authors use two parametric extended spike models, where the second one is more flexible than the first in regard to the shape of the response distribution at both sides of the spike, i.e., the point at which there is a clear division between respondents with positive and negative WTP, which is when price of the public program equals zero. To identify respondents out-of-market, the survey involved an initial filter question: "Would you take the program at no cost?". If respondents answer "No", then these are respondents out-of-market.

data on prescribed burning preferences in Florida 1999-2000, and find that the binary logit model overestimates mean WTP, whereas the double-bounded logit model and Turnbull estimator do not, and work well around negative preferences.

Loomis et al. (2005) also study preferences for fuel treatment programs using survey data from US states. However, as opposed to Nahuelhual-Munoz, et al. (2004) - who combine survey respondents from California and Montana based on the acknowledgement that both are fire-prone states - Loomis et al. (2005) get individual estimates of WTP for California, Florida, and Montana on the basis that each state has different demographic, ecological and wildfire risk profiles. Moreover, Loomis et al. (2005) not only study prescribed burning, but also mechanical fuel reduction programs. As in Nahuelhual-Munoz, et al. (2004), survey respondents were presented with a booklet outlining the benefits of fuel treatment. Then, they would be presented with a dichotomous choice referendum type question, where they had to vote in favour or against the expansion of the fuel treatment program, followed up with a WTP question for a range of bid amounts. Using a binary logit model, the authors find no statistically significant difference across states in response rates for the in-depth interviews. Similarly, no difference was found in the protest and non-protest response patterns[48] across the three states, i.e., respondents' reasons for refusal to pay are similar across the three states. Mean WTP for both prescribed burning and mechanical fuel reduction programs were generally not statistically different from each other across the three states. These were 417, 305, and 382 USD for prescribed burning, and 403, 230, and 208 for mechanical fuel reduction, for California, Florida, and Montana,

[48] Protest responses are those that portray opposition to the government or to paying taxes, or responses that express certainty in that the program would not work. Non-protest responses refer to refusals to pay because of the program not being worth the money, or because they cannot afford it. The authors note that non-protest responses may arise from respondents' assessments that the disutility of smoke outweighs the benefits of wildfire reductions.

respectively. Overall, Loomis et al. (2005)'s findings suggest the mean WTP estimates across these three states may be transferrable to other states in US, i.e., have external validity, and eliminate the need to conduct CV surveys in other states. This would mean that fuel treatment programs, as that of prescribed burning, and wildfire risk may be perceived similarly across fire-prone states.

However, at a more micro level, this last statement may not always hold. Studies looking at differences in preferences for fuel treatment programs across different communities and ethnic groups in the US find mixed results. Loomis, et al. (2004) find no statistically significant difference in mean WTP for prescribed burning in California across African Americans and White households (399 and 505 USD, respectively). Nevertheless, the authors do find that demographic differences play an important role. For instance, response rates were statistically different across Hispanics, African Americans, and White households, but these differences disappear once accounting for demographic differences (age, gender, education, income, and home value). Similarly, African American's mean WTP is halved when White households' demographics are used on African Americans' coefficients. Therefore, the findings suggest that it is not ethnicity or language which generates large differences in WTP, but rather demographics.

Gonzalez-Caban et al. (2007) arrive at similar conclusions when analysing WTP for prescribed burning and mechanical fuel treatment programs elicited by Native Americans and the general population in Montana: no statistically significant difference in median WTP for both fuel treatment programs, but statistically significant differences in response rates, with lower response rates for Native Americans.

On the other hand, when looking at WTP increments for larger reductions in area burnt by wildfires, there do seem to be differences across ethnic groups. For example, Loomis, et al. (2009) find that WTP increments for these larger reductions are three to four times higher for Hispanics than for White households in California, Florida, and Montana (0.83 vs. 0.26 USD for the prescribed burning program and 1.27 vs. 0.27 USD for the mechanical fuel reduction program, per household, per year, for a 100-acre reduction in area burnt). The authors suggest that higher increments in WTP of Hispanic households may be explained by an expectation of there being a low likelihood of paying the full amount of the corresponding tax increase to support the expansion of the fuel treatment programs, given their lower income status in comparison to White households.

The issue of wildfire risk perception is approached by Kaval, et al. (2007). The authors look at prescribed burning preferences in the WUI of Colorado, 2001, using a sample of respondents, almost entirely Caucasians, which is representative of the state's population. Respondents were surveyed on perceived fire danger and frequency, and WTP for prescribed burning. Results suggest that households are not only well aware of wildfire danger and frequency in their areas, but that they also respond to changes in these, i.e., mean WTP increased from 800 USD by 284 USD when households felt their home was at an increased danger from wildfires and increased by 8 USD when households perceived an increase in the frequency of wildfires in the vicinity of their home. Not only were households knowledgeable of wildfire risk to their property, but discussions with respondents revealed that backfiring, i.e., undertaking private prescribed burning on the surrounding of their properties, used to be practiced until it was made illegal by authorities. At the time of the study, a defensible space of 30 metres was allowed, and while there was evidence of the effectiveness in protecting homes, it was not mandatory. Overall, the authors suggest that households are well aware of wildfire risk in their areas, which explains a large mean WTP for prescribed burning[49].

Preferences for wildfire risk management are, however, inextricably entangled with amenity values, e.g., prescribed fires generate disamenities, such as smoke haze and burnt landscapes. The second subgroup of CV studies is devoted to the valuation of forest amenities, particularly in relation to biodiversity and recreation values. Loomis & Gonzalez-Caban (1994; 1997; 1998) study preferences on fuel treatment programs that would be executed on the northern spotted owl's critical habitat. Loomis & Gonzalez-Caban (1994) study preferences in Oregon in regard to fuel treatments within state, whilst Loomis & Gonzalez-Caban (1997; 1998) study preferences in California and New England in regard to fuel treatments in California and Oregon. These three studies look at use and non-use values from forest amenities, and more specifically at the preservation of old-growth forest ecosystems, home to the northern spotted owl, and at threat of catastrophic wildfires. Loomis & Gonzalez-Caban (1994) use the voter-referendum format to get the total economic value of old-growth forest amenities; i.e., the sum of recreation, option, existence and bequest values. On the first set of questions of the survey, authors asked Oregon households to rank the relative importance of recreation, timber provision, and plant and wildlife habitat provision services of old-growth forests. Then, respondents were presented with the fire prevention program, which consists of a better response to any fires, earlier fire

[49] The authors find that almost 90 percent of respondents supported prescribed burning as wildfire management policy. Moreover, Kaval, et al. (2007) point out that, when surveys of Colorado residents were conducted by the United States Forest Service (USFS), findings suggested that the proportion of respondents who support fire suppression at all costs rather than prescribed burning practices was three-fold that of their study. Such a discrepancy can be explained by the scope of respondents: the USFS surveyed Colorado residents in general, whilst the survey by Kaval, et al. (2007) studied residents of the WUI only.

detection systems, and better fire protection. Respondents were told that the yearly area burnt would be halved, from 11 to 5.5 square miles, if the fire prevention program were implemented. Then, respondents would answer “yes” or “no” to questions on whether they would vote in favour or against of implementing the program at several cost options. Findings suggest that the average household in Oregon would be WTP 77 USD for the fire prevention program. Individuals who use the forest for recreational purposes were more likely to pay for the program. The larger the perception of harm to plant and wildlife biodiversity caused by wildfires, the larger the WTP. We must note, however, that the fire protection aspect of the program does not directly mention fuel treatment practices. To be clear, respondents were told a better fire prevention outcome would include fire safety education, enforcement of fire regulations, a greater number of fire patrols, and, importantly, the maintenance of existing firebreaks surrounding old growth forests[50].

On the other hand, Loomis & Gonzalez-Caban (1997; 1998)’s studies do look specifically at the valuation of prescribed burning programs to reduce fire intensity in the old growth forests in question. Both of these studies present respondents with a fire prevention program that includes fire hazard reduction – in addition to providing a better response to any fires, earlier fire detection systems, and better fire protection, as in Loomis & Gonzalez-Caban (1994). The fire hazard reduction aspect of the program consists of mechanical removal of brush and small deadwood on forest floor plus a prescribed fire program every 10 years. Their findings suggest large support for prescribed burning and mechanical fuel reduction programs, with benefits greatly exceeding the costs necessary to implement the program. Knowledge of the existence

[50] Although the authors do not state that firebreaks are maintained for prescribed burning purposes, we know that firebreaks are used for defining the perimeters of prescribed fires.

of the old growth forests and a belief in their importance in maintaining environmental quality were found to significantly boost WTP (Loomis & Gonzalez-Caban, 1997).

Also looking at the benefits of prescribed fires is the study of Loomis et al. (2002), but focused on a particular recreational value: deer harvest and hunting in the San Bernardino National Forest of southern California. This study attempts to evaluate the ecological impacts of prescribed burning over time, in a context where the San Jacinto Ranger District planned to increase prescribed fires by 50 to 100 percent to increase deer population. The authors note that prescribed burning and deer harvest are positively correlated and employ an open-ended question for hunters to elicit their maximum WTP for an additional trip under current and improved conditions. Their findings suggest a total of 2,674 USD marginal benefits from an increase in 1000 acres of prescribed burning, under the assumption of no reduction in wildfire. When assuming a reduction in wildfires, the marginal benefits stem to 3,218 USD.

The review of the existing literature suggests that households living in wildfire prone areas are aware of wildfire risk: low forest density in the immediate vicinity of property is a valuable attribute (Hjerpe, et al., 2016), and WUI residents exhibit stronger support for prescribed burning than the general public (Kaval, et al., 2007). Moreover, there is evidence of positive WTP for fuel treatment programs, even after accounting for any compensation that would need to be paid for those who are not WTP anything for or oppose these programs, likely due to the smoke emissions generated by prescribed burning (Nahuelhual-Munoz, et al., 2004; Loureiro, et al., 2004; Loomis, et al., 2005). Statistically significant differences in WTP across ethnic groups seem to be mainly driven by demographic characteristics (Loomis, et al., 2004; Gonzalez-Caban, et al., 2007; Loomis, et al., 2009) and therefore, valuation of reductions in catastrophic wildfire risk through fuel treatments appear to be universally aligned across states and ethnic groups – with some exceptions noted. Overall, fuel treatment programs seem to receive strong support (Loomis, et al., 2004; Loomis, et al., 2009) and are economically viable (Gonzalez-Caban, et al., 2007; Kaval, et al., 2007). Forest amenities are also valued for households living in wildfire prone regions, and they are WTP for fire prevention programs that reduce the extent of important ecosystem areas that is burnt (Loomis & Gonzalez-Caban, 1994; 1997; 1998), or that enhance recreational benefits, as that of deer hunting (Loomis, et al., 2002).

Importantly, however, the findings from this literature review are applicable to the US only. A wildfire prone country, such as Australia, also deserves to be studied. We also notice that the CV method dominates; in our review, only one study – Hjerpe et al. (2016) – uses market revealed preferences. We recognise that surveys are convenient when trying to understand the reasons behind the resulting WTP estimates. However, we believe such findings should be complemented with revealed preference studies, such as the HPM, because there may be a difference between individuals' desire on how to act and individuals' actions. The latter would be captured by market responses, such as choosing where to live. At last, we also notice that studies on the economic valuation of fuel treatments have stagnated over the last decade: the most recent study we find is that of Hjerpe, et al. (2016). This is worrying considering that wildfire danger and frequency are increasing worldwide (UNEP, 2022).

3.3 PRESCRIBED BURNING IN WESTERN AUSTRALIA

The primary purpose of prescribed burning in WA is protecting lives and property by reducing the build-up of flammable fuel loads, and, therefore, reducing the risk of catastrophic wildfires. Another purpose for which prescribed burning is carried out in WA is the maintenance of biodiversity (DBCA, 2023). Ironically, many who oppose prescribed burning would argue that prescribed burning is harmful to biodiversity.

Other purposes are the rehabilitation of vegetation following an event of disturbance (such as timber harvesting and mining) and to research on fire-environment interactions (DBCA, 2023).

The burning is ‘prescribed’ because it is commended and needs to meet certain conditions. For instance, for regions with distinct seasons, prescribed burning takes place in spring (September to November) and autumn (March to May) when vegetation is high in volume and moisture levels, and weather conditions are cooler and stabler. In northern regions, where seasons are either wet or dry, prescribed burning takes place during the wet season and up to the early dry season (January to June), when winds are easier to predict, vegetation has not yet fully dried, fires tend to be low in intensity, small in extensity, patchy, and likely to extinguish at night-time. Additionally, on the day of the planned prescribed fire, environmental conditions must be assessed to prevent a fire escape; and for that reason, the decision to ignite is made on the same day (DBCA, 2023).

Nevertheless, the decision to ignite a prescribed fire on public land is always preceded by a planning process that involves many stakeholders, including primarily, the Department of Parks & Wildlife Service (DPAW) at the Department for Biodiversity, Conservation, and Attractions (DBCA), which must also respond to wildfires and conduct research on fire behaviour and impacts (DBCA, 2023). Whenever appropriate, the DPAW works in conjunction with the Department of Fire and Emergency Services (DFES) and local governments to undertake prescribed burning (DBCA, 2023). The planning process starts with the development of a Burn Program prepared by DPAW for each region. The Burn Program consists of an indicative annual burn plan, and, for regions in the south-west of WA, a three-year indicative burn plan also[51]. The program

[51] Likely because of the higher forest presence and population in the area.

must then be approved and published on the DPAW's website. For each burn identified by the program, a plan is formulated. This plan consists of identifying all the preliminary work required before the prescribed fire takes place, such as identifying fuel loads and conditions, fauna and rare flora species, suitable weather conditions for ignition, and establishing burn objectives and success criteria for posterior assessment. The next step is the ignition, which must be approved on the day of the burn (DPAW, n.d.). Besides weather conditions, other criteria are factored in when deciding whether or not to approve the ignition, including a consideration of past fires over the landscape (DBCA, 2023), from which we interpret that the DBCA accounts for any wildfires occurring in the interim, i.e., that happened since the burn plan was formulated. Depending on weather conditions, ignition may be manual, aerial, or a mixture of both. Once ignition has occurred, the DFES publishes the Warnings & Incidents map on the Emergency WA website (DFES, 2023) to inform the general public of active smoke alerts and prescribed fires. Finally, the burn is assessed; for example, if the prescribed fire is to be implemented as an even mosaic of burn patches of up to 500 hectares, success may be assessed through satellite imagery.

Prescribed fires are more than just the outcome of a planning process; each prescribed fire on public land is part of the fire management strategy of WA, which is focused on community and biodiversity protection. Three important points are acknowledged in the fire management strategy of WA. First, that communities expect land managers to protect infrastructure under threat of wildfires at the same time as climate change is augmenting wildfire risk and residential developments closer to bushland are increasing in number. Second, that communities also exert pressure on land managers to protect natural values at the same time as there is an increasing number of people using green areas (forests, parks, and reserves). Third, that communities are expanding, and their experiences and expectations regarding fire management are increasingly divergent. In essence, the fire management strategy of WA consists of managing wildfire risk through fuel loads. Small areas may be subject to mechanical fuel reduction – i.e., the action of reducing available fuel through manual or machine methods (NPS, 2023) - and weed control, but most of the land managed by the department is treated via prescribed burning, which is less costly. The prescribed burning strategy is supported by peer-reviewed research and consists of the creation of a mosaic of fuel ages and structures, "*most effective when at least 45 percent of the fuel across the forest landscape is maintained at less than six years since last burnt*". For this approach to be successful, a target of 200 thousand hectares of land in south-west forests needs to be reached on an annual basis (DBCA, 2019)

As noted, major concerns amongst the community are the impact of prescribed burning on biodiversity values and infrastructure. Given this concern, prescribed fires on native forests are implemented on mosaic patches and over spring when fuel and soil is most moist. Such combination generates prescribed fires of low intensity and with unburnt pockets that provide refuge and travel corridors for wildlife to safely escape whilst preserving important biodiversity and habitat values (Meinema, 2023). Regarding infrastructure protection, the DBCA states that prescribed burning is a 'very' effective tool for managing wildfires because it reduces fuel loads, which are directly linked to fire behaviour. If fire behaviour is such that flames are over three metres high or travelling at a speed over 200 metres per hour, suppression efforts are unlikely to be successful. However, if the fire runs into areas recently burnt, suppression efforts are likely to succeed because fuel loads are low. For instance, the Perth Hills Bushfire of 2011 was limited in destruction precisely because prescribed burning had been undertaken in strategic locations only four years before (DBCA, 2023).

The DBCA fire management strategy and corresponding efforts to protect communities and biodiversity via prescribed burning are agreeable for some. For instance, Burrows & McCaw (2013) claim that prescribed burning is an effective tool for managing the risk of wildfires on communities and on vegetation, soil, and ecosystem services. Boer, et al. (2009) study fire history on a eucalypt forested area in WA over a period of 52 years and find that prescribed burning reduced the incidence and extent of unplanned fires for up to six years since last burn; findings which are in line with the six-year mark identified by field practitioners. Moreover, wildfire disasters can also trigger a revaluation of prescribed burning. The Special Inquiry into the 2016 Waroona Fire reports that, for a range of reasons, the annual burning targets in land management zones (LMZs) A, B, and C had not been met almost every year over the last 12 years prior to the fire[52], and that prescribed fires remain to be the "best practice to reduce the severity of fire over broad forest landscapes" (Government of Western Australia, 2016, p. 91).

3.4 METHODOLOGY

We implement the hedonic price model (HPM), first characterised by Rosen (1974) as a model of product differentiation where goods possess utility-bearing attributes, for which no explicit market exists, and yet, buyers and sellers make an implicit trade of these. Jobs, cities, and properties are examples of heterogeneous goods that possess multiple attributes that, when consumed, give rise to certain level of utility

[52] The DBCA prescribed burning target is allocated across three zones managed by the DPAW, labelled as LMZs A, B, and C; each defined within a specified distance from the edge of the populated area, in the form of concentric buffers, LMZ A being the closest to the populated area, followed by LMZ B and then by LMZ C (dataWA, 2021).

(Greenstone, 2017). The higher the utility level derived from an attribute, the higher the hedonic price. In the context of our study, property price (P) for property h sold at time t is expressed as a function of perceived wildfire risk (r), amenity levels (a), and a vector of time-invariant features ($\overline{Z}$); where r, a, and $\overline{Z}$ are the utility-bearing attributes:

$$P_{ht} = f\,(r_{ht},\, a_{ht}, \overline{Z_h}) \qquad (3.1)$$

Equation **(3.1)** is the hedonic price function (HPF). The relationship between r and utility levels is negative, whereas the relationship between a and utility levels is positive, i.e., $\frac{\partial P_{ht}}{\partial r_{ht}} < 0$ and $\frac{\partial P_{ht}}{\partial a_{ht}} > 0$.

Note that, as opposed to $\overline{Z}$, r and a vary over time. This is because both r and a are a function of property h's exposure to past prescribed and wildfires (pf_h and wf_h, respectively), i.e., past pf_h and wf_h alter risk perceptions and amenity levels. We will go on to use two indicators of exposure: area burnt and number of fires around the property. We do this because risk perception is altered by judgements on consequence and probability of occurrence. Area burnt because it is an indication of consequence, and number of fires an indication of probability of occurrence, both of which may be picked up by households. Nonetheless, consequence and probability judgements are not independent from each other, e.g., a very small fire may be completely ignored by households and hence not accounted for frequency judgements. Moreover, in our model, we account for the incremental exposure to fires[53]. In other words, we include fires recorded between time $l = t - n$ and time $m = l + 1$, where $n = 1, 2, \ldots, N$ and is expressed in calendar years, i.e., we include fires occurring between years 0 and 1, 1

[53] The decision to account for incremental impacts of fire on property price follows that incremental impacts would allow to observe how the effect of past fires diminishes over time.

and 2, ..., and so on prior to the sale date. Equations **(3.2)** and **(3.3)** below show r and a as a function of both pf and wf between time l and time m, and equations **(3.4)** and **(3.5)** develop the time notations in **(3.2)** and **(3.3)** for all values of n.

$$r_{ht} = f\left(pf_{h_l}^{\ m}, wf_{h_l}^{\ m}\right) for\ n = 1, 2, \dots, N \tag{3.2}$$

$$a_{ht} = f\left(pf_{h_l}^{\ m}, wf_{h_l}^{\ m}\right) for\ n = 1, 2, \dots, N \tag{3.3}$$

$$r_{ht} = f\ (pf_{h_{t-1}}^{\ t-0}, pf_{h_{t-2}}^{\ t-1}, \dots, pf_{h_{t-N}}^{\ t-N-1}, wf_{h_{t-1}}^{\ t-0}, wf_{h_{t-2}}^{\ t-1}, \dots, wf_{h_{t-N}}^{\ t-N-1}) \tag{3.4}$$

$$a_{ht} = f\ (pf_{h_{t-1}}^{\ t-0}, pf_{h_{t-2}}^{\ t-1}, \dots, pf_{h_{t-N}}^{\ t-N-1}, wf_{h_{t-1}}^{\ t-0}, wf_{h_{t-2}}^{\ t-1}, \dots, wf_{h_{t-N}}^{\ t-N-1}) \tag{3.5}$$

Given that prescribed fires reduce fuel load, and a reduction in fuel load is equivalent to a reduction in wildfire risk, we expect the derivative of r with respect to pf_l^m to be negative, i.e., $\frac{\partial r_{ht}}{\partial pf_{h_l}^{\ m}} < 0$. Moreover, given that fuel accumulation increases since last burn, we expect $\left|\frac{\partial r_{ht}}{\partial pf_{h_l}^{\ m}}\right|$ to be greater for more recent exposure, i.e., $\left|\frac{\partial r_{ht}}{\partial pf_{h_{t-1}}^{\ t-0}}\right| > \left|\frac{\partial r_{ht}}{\partial pf_{h_{t-2}}^{\ t-1}}\right| > \cdots > \left|\frac{\partial r_{ht}}{\partial pf_{h_{t-N}}^{\ t-N-1}}\right|$. Prescribed fires, however, come at a cost in the shape of smoke, road closures, and burnt landscapes and wildlife habitats. Therefore, we expect the derivative of a with respect to pf_l^m to be negative[54], i.e., $\frac{\partial a_{ht}}{\partial pf_{h_l}^{\ m}} < 0$. Because these amenity disruptions are transitory, we expect $\left|\frac{\partial a_{ht}}{\partial pf_{h_l}^{\ m}}\right|$ to be greater for more recent exposure.

54 We are aware that prescribed fires may also increase amenity levels, as those related to recreational values, e.g., deer harvesting, as studied by Loomis, et al. (2002). However, news articles on Western Australian's experience with prescribed fires reviewed in the second section of this paper prevents us from expecting that recreational benefits would dominate over the disamenities.

Wildfire impacts are trickier to hypothesize. On one hand, wildfires may increase r because of availability heuristic, i.e., events that are easier to retrieve are judged as more frequent or probable (Tversky & Kahneman, 1974)[55], and we can think of wildfires as events easy to retrieve because of the media coverage received and the distress on those who experienced the wildfire firsthand, either as a near-miss or a direct-hit. On the other hand, wildfires may reduce r if households are knowledgeable of the risk reduction effect that results from the reduction in fuel load, or if they feel more resilient after the event[56]. Both counteracting effects should be greater for more recent exposure, i.e., availability bias and fuel load reduction should both be higher for wf over time periods closer to sale date. We do not know which effect dominates, and therefore make no hypothesis on the sign of $\frac{\partial r_{ht}}{\partial w f_{h_l}^{m}}$. Furthermore, and the same as prescribed fires, wildfires reduce amenity levels. Due to its unplanned nature, wildfires are more likely to generate long-term impacts, such as the loss or harm of vegetation and wildlife. Therefore, we expect the derivative of a with respect to wf_l^m to be negative and larger than the derivative of a with respect to pf_l^m, i.e., $\frac{\partial a_{ht}}{\partial w f_{h_l}^{m}} < 0$ and $\left|\frac{\partial a_{ht}}{\partial w f_{h_l}^{m}}\right| > \left|\frac{\partial a_{ht}}{\partial p f_{h_l}^{m}}\right|$.

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55 The impacts of pf and wf on r and a may be influenced by availability bias. Availability bias occurs when an event is easier to retrieve and therefore judged as more frequent or probable (Tversky & Kahneman, 1974).

56 Impacts of wf on r may be influenced by the way households interpret near-miss events. According to Tinsley et al. (2012), vulnerability feelings may arise if a near-miss is interpreted as a disaster that "almost happened". Nonetheless, the opposite may hold true: if a near-miss is interpreted as a disaster that "did not happen", then resiliency feelings may arise. If resiliency feelings arise, we may expect a decrease in risk perception. On the other hand, if vulnerability feelings arise, we may expect an increase in risk perception. Households who were not directly hit by the wildfire experience the event as a near-miss, and we think it's sensible to assume this is the case for most households of properties in our sample.

We make four important assumptions for our model. First, we assume a semi-logarithmic functional form for the HPF[57]. Second, we assume that both r and a have linear functional forms. This assumption is made for analytical convenience. Third, that any pf and wf that occurred more than six years before sale date have no impact on r or a, and therefore no impact on P. This third assumption is based on the following: i) Boer et al. (2009)'s findings that prescribed burning reduces wildfire risk for up to six years, and ii) the DBCA's target to maintain fuel age at a maximum of six years since last burnt, based on both peer-reviewed and field evidence. Fourth, that pf and wf more than 5 km away from the property's location have no impact on r or a, and therefore no impact on P. This fourth assumption is supported by our previous findings that only properties within a 5 km distance from burn scars experience a price mark-up (see **CHAPTER 1** in this thesis). The confluence of the third and fourth assumption leads us to define fire 'exposure' as inclusive only of fires with a burn scar within a 5-km radius from the property, having that fire occurred within any of the first six years prior to sale date, e.g., ${pf_h}_{t-2}^{t-1}$ refers to exposure to prescribed fire burn scars that occurred on the 2nd year prior to sale date and within a 5-km radius from the property. From this point forward, we refer to 'exposure' in such terms. Additionally, we acknowledge that we cannot disentangle r from a. We can only distinguish between lagged values of pf and wf.

Hence, P is expressed as a function of lagged values of pf and wf, along with $\overline{Z}$, which is accounted via property fixed effects (FE), i.e., Φ_h . Property FE allows us to account for observed and unobserved time invariant characteristics. Notice that it is no longer possible to sign the coefficients because r and a are entangled on pf and wf. More

[57] This is usual practice. It is also recommended due to its simplicity and better performance under potential omitted variable bias (Cropper, et al., 1988; Palmquist, 2005).

specifically, the sign of the coefficients on the lagged values will depend upon which of the several potential effects described above dominates[58]. We also include fiscal year (y) and season (s) FE to account for economic and political events and weather characteristics that may impact the housing market. Our final model for property h sold at time t is therefore that in equation **(3.6)** below, where α is a constant and μ is an error term:

$$\ln P_{ht} = \alpha + \sum_{n=1}^{6} \beta_n pf_{h_l}^{\ m} + \sum_{n=1}^{6} \theta_n wf_{h_l}^{\ m} + \Phi_h + \sigma_y + \delta_s + \mu_{ht} \tag{3.6}$$

As noted above, there is a difference in the way prescribed fires and wildfires alter risk perception and amenity values. We believe this difference emerges from the nature of their occurrence: prescribed fires are planned whilst wildfires are not. Therefore, the attitude toward prescribed fires may be different across households with and without past wildfire exposure, for example, and vice versa. In addition to attitude, wildfire risk depends on fuel age, which is affected by exposure to past fires. In other words, prescribed fires and wildfires are substitutes for risk reduction effects. Therefore, experience with past wildfires may affect preferences for prescribed fires, and vice versa.

Prescribed and wildfires are therefore interpreted differently depending on households' prior experience, where experience is defined as exposure over the entire six-year period prior to sale date[59]. To deal with this experiential difference, we use our basic specification from equation **(3.6)** but look at five subsamples of interest. The

[58] For example, if prescribed fires are successful in reducing risk perception and households value this risk reduction effect more than any disamenity impact, we should see an increase in price, i.e., β_n should be positive. Otherwise, β_n should be negative.
[59] In other words, the cumulative exposure between the sale date and six years before sale date. Hence, if we say, for example, that a property has no wildfire experience, it means that the property has had no exposure to wildfires throughout the whole six-year period prior to sale date. Conversely, a property with wildfire experience is one with exposure to at least one wildfire over the entire six-year period prior to sale date.

first subsample has no restriction, so it really is the entire sample (all observations). The second and third subsamples are restricted to observations with and without previous wildfire experience, respectively. At last, the fourth and fifth subsamples are restricted to observations with and without previous prescribed fire experience, respectively. Each subsample has its own estimation equation (five in total). **Table 3.4.1** below indicates the subsample for all of our estimation equations.

Table 3.4.1: Equations

Equation	Subsample
(I)	All observations
(II)	Observations with wildfire experience
(III)	Observations without wildfire experience
(IV)	Observations with prescribed fire experience
(V)	Observations without prescribed fire experience

Full definitions for the variables included in our model are described in **Table 3.4.2** below. From this point forward, we refer to ${pf_{h}}_{l}^{m}$ and ${wf_{h}}_{l}^{m}$ as our treatment variables.

Table 3.4.2: Definition of variables

Variable	Units	Definition	Example
$\boldsymbol{ln\,P_{ht}}$	nominal monetary	log of market sale price	-
$\boldsymbol{{pf_{h}}_{l}^{m}}$	• area burnt • number of fires	exposure to prescribed fire between time $\boldsymbol{l}$ and time $\boldsymbol{m}$	For $\boldsymbol{n = 1}$: $\boldsymbol{l = t - 1}$ $\boldsymbol{m = t - 0}$ $\boldsymbol{{pf_{h}}_{l}^{m} = {pf_{h}}_{t-1}^{t-0}}$
$\boldsymbol{{wf_{h}}_{l}^{m}}$	• area burnt • number of fires	exposure to wildfire between time $\boldsymbol{l}$ and time $\boldsymbol{m}$	For $\boldsymbol{n = 6}$: $\boldsymbol{l = t - 6}$ $\boldsymbol{m = t - 5}$ $\boldsymbol{{pf_{h}}_{l}^{m} = {pf_{h}}_{t-6}^{t-5}}$

3.5 DATA

The central piece of our data is the property market dataset for residential properties provided by Australian Property Monitors (APM) for sales between 2010 and 2019. This dataset includes sale price in Australian dollars (AUD), sale date, and a range of structural attributes such as area, number of bedrooms, bathrooms, and parking spaces, amongst many others. Critically for our purposes, we created a property ID to identify repeat sales of the same property. For neighbourhood and environmental attributes, we use several GIS datasets provided by the Government of Western Australia, and with the aid of the properties' latitudes and longitudes provided by APM, we implement a spatial analysis in ArcMap – a GIS application to display, explore, modify and analyse spatial datasets - to get the Euclidean distance between the property and nearest public beach, forested area, and wetland, public bus and train stops, school, and the edge of central Perth. We also identify whether or not the property is within urban land and an LMZ. Latitudes and longitudes of properties are also used to identify fire exposure.

To obtain the fire records of interest, we use the *DBCA Fire History* dataset published by the DBCA[60]. This dataset is classified as "official" under the Government of Western Australia's information classification policy. It contains records of fire events occurring since 1922, although some historical records are missing due to unobtainable historic map sheets. The geographic extent of the dataset covers the entire state of WA since 2006. Earlier records correspond to fire events captured on

[60] We downloaded the *DBCA Fire History* dataset from the Government of Western Australia's data catalogue (*Data WA)* website (Government of Western Australia, 2023) on the 9th of November of 2022, and according to the properties of the shapefiles downloaded, the records were last updated the 25th of July of 2022. At that point in time, a total of 50,177 fire events were recorded between 2004 and 2019. Of these, more than 40 percent are recorded as wildfires and 8 percent are recorded as prescribed fires, whilst more than 29 percent are recorded as of unknown type.

land managed by the DBCA and, where available, land not managed by the DBCA. Generally, the dataset is updated biannually, around January and July.

The fire events recorded are of five types: wild, prescribed, mining rehabilitation, plantation, or unknown fires. We keep only wild and prescribed fire records. Each record is represented by a GIS vector-based polygon. For each record, a date is provided, along with a cause, purpose, and total area in hectares, amongst other descriptive data. For prescribed burns ignited multiple times, the date of first ignition is recorded. On the other hand, for wildfires, the date corresponds to that when the fire was first recorded in official government system records and may not align with date of first ignition nor completion.

The cause attribute corresponds to the cause of wildfires, e.g., deliberate, escapes from prescribed burns, accidental, lighting, etc. For fire records different to wildfires, a "no cause, event was a prescribed burn" value is imputed. The purpose attribute corresponds to the purpose of fires different to wildfires, i.e., strategic protection, biodiversity management, vegetation management, etc. For wildfires, a "no cause, event was a bushfire" value is recorded for this attribute. The following paragraph describes the processes followed in ArcMap and QGIS to create two datasets indicating the fire polygon areas in square metres (m^2) within 5 km of each residence from our property market dataset, one for wildfires and one for prescribed burns.

Since we are interested in the impact of wildfires and prescribed burns events occurring six years prior to sale date of the property, we make a careful selection of fire records in ArcMap. First, given that our property market data ranges from 2010 to 2019, we select fire records from 2004 enabling us to work with all observations in our dataset. To create the wildfire dataset, we select all fire events recorded as wildfires, with a cause attribute different to “no cause, event was a prescribed burn”, and with purpose attribute equal to “no cause, event was a bushfire” to avoid selecting prescribed burns or other types of fires mistakenly recorded as wildfires. On the other hand, to create the prescribed burn dataset, we select all fire events recorded as prescribed burns, with cause attribute equal to “no cause, event was a prescribed burn”, and with purpose attribute different to “no cause, event was a bushfire”. We also exclude all records with cause and purpose attributes equal to “Unknown (historic data)”. Then, we proceed to create 5-km buffer zones surrounding the residential properties of our property market data and to create an intersection of these buffer zones for each of our fire datasets in order to identify all fires entirely or partially within the buffer zones. To do so, the “Buffer” and “Intersect” tools from the “Proximity” and “Overlay” tool sets were used. Finally, for each fire dataset, we use the “Calculate Geometry” tool in QGIS to create a new attribute field with the area in m^2 of the fire polygons that fall within the 5-km buffer zone.

To get our final dataset, we merge the prescribed fire and wildfire datasets to the property market dataset with structural, neighbourhood, and environmental attributes. The dataset has a total of 89,419 observations (sales) for 78,088 unique properties, of which 10,571 properties were sold more than once between 2010 and 2019, respectively.

A total of 2,258 wildfires and 1,202 prescribed fires generate exposure to fire to at least one observation of our sample of properties. As shown in **Table 3.5.1** below, the large majority of our sample (70%) has been exposed to fire, i.e., to prescribed fires, wildfires, or both. Additionally, we see that wildfire exposure is clearly larger than prescribed fire exposure, suggesting that households are most familiar with wildfires than with prescribed fires - 77.3% of our sample has no exposure to prescribed fires.

Table 3.5.1: Exposure to fire

$pf_{h\,t-6}^{\;t-0} > 0$	$wf_{h\,t-6}^{\;t-0} > 0$	Obs.	%
No	No	26,633	29.8
Yes	Yes	18,407	20.6
No	Yes	42,439	47.5
Yes	No	1,940	2.2
		89,419	**100**

Indeed, wildfire exposure in terms of number of fires for the average property in WA is more than four times larger than prescribed fire exposure. Interestingly, however, area burnt by prescribed fires is 1.5 times larger than area burnt by wildfires – see **Table 3.5.2** below[61].

We reach similar conclusions for the average treated property in WA, i.e., exposure to wildfires is also greater than exposure to prescribed fires, when looking at number of fires as exposure indicator, but the opposite is true when looking at area burnt– see **Table 3.5.3** below.

[61] The average property has been exposed to 0.66 prescribed fires with 906,559 m^2 of area burnt and 2.94 wildfires with 600,834 m^2 of area burnt.
2.94/0.66 =4.45 and 906559/600834 = 1.51

Table 3.5.2: Summary statistics for all observations

	Variable	Obs.	Panel A number of fires				Panel B area burnt (m²)			
			Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Prescribed fires	${pf_h}_{t-1}^{t-0}$	89,419	0.13	0.47	0	6	158,074	995,326	0	26,300,000
	${pf_h}_{t-2}^{t-1}$	89,419	0.12	0.46	0	7	160,279	1,001,058	0	22,800,000
	${pf_h}_{t-3}^{t-2}$	89,419	0.11	0.43	0	6	149,371	1,003,330	0	22,900,000
	${pf_h}_{t-4}^{t-3}$	89,419	0.10	0.43	0	11	146,983	1,025,993	0	28,000,000
	${pf_h}_{t-5}^{t-4}$	89,419	0.10	0.45	0	23	144,733	1,000,883	0	25,900,000
	${pf_h}_{t-6}^{t-5}$	89,419	0.10	0.44	0	13	147,119	989,239	0	26,900,000
	$\boldsymbol{{pf_h}_{t-6}^{t-0}}$	**89,419**	**0.66**	**1.86**	**0**	**28**	**906,559**	**3,674,209**	**0**	**54,600,000**
Wildfires	${wf_h}_{t-1}^{t-0}$	89,419	0.62	1.27	0	15	118,294	1,237,537	0	57,300,000
	${wf_h}_{t-2}^{t-1}$	89,419	0.51	1.16	0	15	106,489	1,188,905	0	56,900,000
	${wf_h}_{t-3}^{t-2}$	89,419	0.50	1.14	0	13	105,427	1,203,292	0	55,300,000
	${wf_h}_{t-4}^{t-3}$	89,419	0.47	1.10	0	14	104,130	1,183,044	0	49,600,000
	${wf_h}_{t-5}^{t-4}$	89,419	0.43	1.02	0	14	88,294	1,008,304	0	37,200,000
	${wf_h}_{t-6}^{t-5}$	89,419	0.40	0.96	0	13	78,200	846,055	0	41,100,000
	$\boldsymbol{{wf_h}_{t-6}^{t-0}}$	**89,419**	**2.94**	**4.59**	**0**	**54**	**600,834**	**3,658,841**	**0**	**83,800,000**

Table 3.5.3: Summary statistics for treated observations

			Panel A number of fires				Panel B area burnt (m²)			
	Variable	Obs	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Prescribed fires	$pf_{h_{t-1}}^{t-0}$	8,328	1.401	0.788	1	6	1,697,265	2,832,922	3.66	26,300,000
	$pf_{h_{t-2}}^{t-1}$	7,916	1.405	0.793	1	7	1,810,508	2,886,707	0.87	22,800,000
	$pf_{h_{t-3}}^{t-2}$	6,898	1.390	0.798	1	6	1,936,299	3,096,888	0.01	22,900,000
	$pf_{h_{t-4}}^{t-3}$	6,373	1.421	0.867	1	11	2,062,306	3,289,580	4.52	28,000,000
	$pf_{h_{t-5}}^{t-4}$	6,109	1.442	0.991	1	23	2,118,499	3,237,787	0.06	25,900,000
	$pf_{h_{t-6}}^{t-5}$	5,940	1.459	0.978	1	13	2,214,683	3,186,533	0.32	26,900,000
	$\boldsymbol{pf_{h_{t-6}}^{t-0}}$	**20,347**	**2.895**	**2.961**	**1**	**28**	**3,984,056**	**6,860,640**	**3.79**	**54,600,000**
Wildfires	$wf_{h_{t-1}}^{t-0}$	29,246	1.899	1.591	1	15	361,683	2,143,500	0.24	57,300,000
	$wf_{h_{t-2}}^{t-1}$	24,694	1.861	1.536	1	15	385,606	2,238,504	0.17	56,900,000
	$wf_{h_{t-3}}^{t-2}$	24,502	1.821	1.523	1	13	384,751	2,275,252	0.17	55,300,000
	$wf_{h_{t-4}}^{t-3}$	24,100	1.759	1.485	1	14	386,355	2,254,787	0.30	49,600,000
	$wf_{h_{t-5}}^{t-4}$	22,904	1.673	1.402	1	14	344,707	1,970,005	1.30	37,200,000
	$wf_{h_{t-6}}^{t-5}$	22,150	1.615	1.315	1	13	315,691	1,677,745	0.05	41,100,000
	$\boldsymbol{wf_{h_{t-6}}^{t-0}}$	**60,846**	**4.317**	**4.998**	**1**	**54**	**882,983**	**4,407,336**	**0.00**[a]	**83,800,000**

[a] There are two observations whose 5-km buffer intersects with wildfire burn scars, and for which the area of the wildfire burn scars within the buffer zone is smaller than 0.005 m² and therefore recorded as 0.00 m².

3.6 RESULTS

In this section we present a set of regression results for our two different indicators of exposure. Panel A presents the results for number of fires as the exposure indicator and Panel B presents the results for area burnt in m^2. For simplicity, we interpret coefficients for area burnt in terms of km^2. All equations include property, fiscal year, and season FE. Reported standard errors are robust and adjusted for clusters in Property IDs. We adjust standard errors for clusters in Property IDs because treatment (exposure to fire) is heterogeneous at the property level, i.e., it is properties, and not observations, which are exposed to fire over time[62].Additionally, we present all three measures of R^2: within, between, and overall. Since we are using FE to account for time-invariant characteristics of each unit, the within measure is the most relevant because we are interested in the goodness of fit of our model for explaining variation of property prices across time, within each property unit[63].

Table 3.6.1 below presents our main results. Here we include the entire sample of observations. Findings suggest that the higher the degree of exposure to prescribed fires over the recent years, the higher the property's sale price. This is especially true for exposure over the first two years prior to sale date. Although this positive relationship between degree of fire exposure and property price is captured by both exposure indicators, we see that the number of fires has a higher impact on sale price. For the average property in WA, a marginal increase in the number of fires is associated with a property price increase of 1.2 and 2.6 percent for prescribed fires occurring over the first and second year, respectively. Similarly, a marginal increase in

[62] Recent evidence suggests that cluster adjustments are only effective when there is variation in treatment within clusters (Abadie, et al., 2023).

[63] The R^2 between would instead provide an indication of goodness of fit for explaining differences in property prices between units. The R^2 overall, on the other hand, would give a weighted average.

km2 of area burnt increases property price by 0.7 for prescribed fires occurring over any of the first two years prior to sale date. These results are significant at the 5 percent level or lower.

Table 3.6.1: Main results

	Panel A number of fires	Panel B area burnt (m²)
Equation	I	I
Sample	all observations	all observations
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$
pf_{t-1}^{t-0}	0.012**	6.99e-09***
	(0.005)	(2.68e-09)
pf_{t-2}^{t-1}	0.026***	6.68e-09***
	(0.005)	(2.14e-09)
pf_{t-3}^{t-2}	0.008	1.93e-09
	(0.005)	(2.36e-09)
pf_{t-4}^{t-3}	0.007	7.74e-10
	(0.006)	(2.87e-09)
pf_{t-5}^{t-4}	-0.003	-2.52e-09
	(0.006)	(2.11e-09)
pf_{t-6}^{t-5}	0.003	-2.38e-09
	(0.005)	(2.17e-09)
wf_{t-1}^{t-0}	0.011***	8.55e-10
	(0.002)	(1.33e-09)
wf_{t-2}^{t-1}	0.019***	3.25e-09
	(0.002)	(2.60e-09)
wf_{t-3}^{t-2}	0.011***	1.49e-09
	(0.002)	(1.81e-09)
wf_{t-4}^{t-3}	0.010***	-5.87e-09***
	(0.002)	(2.26e-09)
wf_{t-5}^{t-4}	0.010***	-8.70e-09***
	(0.002)	(2.45e-09)
wf_{t-6}^{t-5}	0.005**	-4.52e-09*
	(0.002)	(2.55e-09)
α	12.870***	12.900***
	(0.010)	(0.009)
Observations	89,419	89,419
Property IDs	78,088	78,088
R^2 within	0.083	0.072
R^2 between	0.002	0.002
R^2 overall	0.003	0.003

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Monetary impacts are also larger when we use the number of prescribed fires as exposure indicator, rather than area burnt. In particular, the average property in WA, having been exposed to 0.13 and 0.12 prescribed fires over the first and second year prior to sale date, experiences a price increase of 657 and 1371 AUD, respectively. These figures are smaller when we use area burnt as exposure indicator: 467 AUD for the first year, and 452 AUD for the second year – see **Table 3.6.2** below. We believe that the larger impacts for number of fires reveals that households are generally more susceptible to the frequency component of risk, rather than consequence[64]. This also explains the larger R^2 we get when using number of fires, instead of area burnt, as exposure indicator.

Table 3.6.2: Main results - Average impacts

variable	exposure indicator	mean exposure	estimated coefficient[a]	average impact (%)[b]	AUD[c]
pf_{t-1}^{t-0}	number of fires	0.130	0.012	0.156	657.336
pf_{t-2}^{t-1}	number of fires	0.124	0.026	0.325	1371.458
pf_{t-1}^{t-0}	area burnt	158,074.000	0.00000000699	0.110	466.821
pf_{t-2}^{t-1}	area burnt	160,278.900	0.00000000668	0.107	452.341
wf_{t-1}^{t-0}	number of fires	0.621	0.011	0.709	2997
wf_{t-2}^{t-1}	number of fires	0.514	0.019	0.963	4069
wf_{t-3}^{t-2}	number of fires	0.499	0.011	0.549	2318
wf_{t-4}^{t-3}	number of fires	0.474	0.010	0.452	1910
wf_{t-5}^{t-4}	number of fires	0.429	0.010	0.444	1875
wf_{t-6}^{t-5}	number of fires	0.400	0.005	0.217	918
wf_{t-4}^{t-3}	area burnt	104,129.500	-0.00000000587	-0.061	-258
wf_{t-5}^{t-4}	area burnt	88,294.080	-0.00000000870	-0.077	-325

[64] The consequence component might have a larger impact for wildfire disasters, where area burnt is large and the event is featured in the media. However, for other wildfires, area burnt may be deemed relatively unimportant. We think it is important to note, however, that with climate change we can expect an increase in the frequency of wildfire disasters, making the frequency and consequence components of risk harder to disentangle.

Table 3.6.2: Main results - Average impacts

variable	exposure indicator	mean exposure	estimated coefficient[a]	average impact (%)[b]	AUD[c]
wf_{t-6}^{t-5}	area burnt	78,199.860	-0.00000000452	-0.035	-149

[a] estimated coefficients are those in **Table 3.6.1**.
[b] average impact (%) is calculated as: (mean exposure) x (estimated coefficient) x 100
[c] average impact (AUD) is calculated as (average impact (%))/100*(mean price), where mean sale price is 422,486.8 AUD.

Importantly, prescribed fires occurring more than two years prior to sale date have no significant impact on sale price. We believe this is because of the decreasing nature of risk reduction effects over time, i.e., given that fuel age of vegetation increases with time since last burn, risk reduction effects are at its peak when the prescribed fire is completed, and then begin to decrease. Another possibility is that, due to availability heuristics, recent prescribed fires are easier to retrieve, and so have a higher impact.

We nevertheless notice that, when using number of fires as exposure indicator, prescribed fires over the second year have a higher impact on property price than those occurring over the first year[65]. This defies our explanation that more recent prescribed fires have higher impacts because of their risk reduction effects. Yet, we believe this is because disamenity impacts – such as smoke haze, road closures, or the view of burnt vegetation – are also higher for the first year. Hence, although risk reduction effects dominate over disamenity impacts for the first two years, it may be that it dominates to a lesser extent over the first year, i.e., $\left(\frac{\partial r_{ht}}{\partial pf_{h_{t-2}^{t-1}}} - \frac{\partial a_{ht}}{\partial pf_{h_{t-2}^{t-1}}}\right) > \left(\frac{\partial r_{ht}}{\partial pf_{h_{t-1}^{t-0}}} - \frac{\partial a_{ht}}{\partial pf_{h_{t-1}^{t-0}}}\right)$.

Property prices are also higher for properties with a higher degree of wildfire exposure, but only when using number of fires as exposure indicator. For the average property in WA, one additional wildfire is associated with a property price increase between

[65] The 95 percent confidence interval for these two coefficients do not overlap, meaning that they are statistically different from each other.

0.5-1.9 percent for wildfires occurring over the first six year prior to sale date, with monetary impacts ranging between 918-4069 AUD – see Panel A in **Table 3.6.1** and **Table 3.6.2**. These coefficients are also significant at the 5 percent level or lower.

We notice that, in contrast with prescribed fires, the positive relationship between number of wildfires and property price is long-lasting, i.e., wildfires as old as six years prior to sale date continue to be associated with higher property price at the moment of sale. This might be due to the unplanned nature of wildfires. In particular, it could be that, given the unplanned nature of wildfires, wildfire exposure is subject to higher uncertainty of outcomes, compared to prescribed fires[66]. We believe it is plausible that unplanned and risky events are easier to retrieve, i.e., are more available in one's mind, even if the event is not so recent.

As with prescribed fires, most recent wildfires also exhibit larger coefficients than those further away in time, with the exception of those occurring over the second year prior to sale date. Here too we believe this is due to the decreasing nature of risk reduction effects, availability heuristics, and the dynamic between risk reduction effects and disamenity impacts over time.

Conversely, we find no statistically significant impact for the exposure to an additional m^2 of area burnt by recent wildfires, i.e., those occurring over the first three years prior to sale date[67]. For the following three years, the impact is negative and statistically significant, with average price discounts of 258, 325, and 149 AUD for wildfires

[66] Prescribed fires, being planned, are generally certain, i.e., the household generally knows the fire will not reach its home. This is false only with prescribed fire escapes, which in our dataset are classified as wildfires. Wildfires, on the other hand, are unplanned and therefore the risk of property damage is higher.

[67] We think this owes to the smaller R^2 of the model for area burnt as indicator of exposure. Nevertheless, one possible explanation for positive but statistically insignificant coefficients is that risk reduction effects, although strong soon after wildfires, are opaqued by vulnerability feelings – as findings in **CHAPTER 1** suggest. This would of course only be a reasonable explanation for large wildfires, which is why these findings arise only when we use area burnt as indicator of exposure.

occurring over the fourth, fifth, and sixth year prior to sale date, respectively. We immediately notice there is an apparent contradiction here. On one side, we find an increase in sale price for additional exposure in terms of the number of wildfires. On the other side, we find a decrease in sale price for additional exposure to area burnt by wildfires. Again, this might be explained by the unplanned nature of wildfires, i.e., as the area burnt by wildfires increases, so does the likelihood of the fire reaching homes and generating damage. It would therefore make sense that households show, as **Table 3.6.1** suggests, a positive preference for a higher number of wildfires, but of smaller size.

Now we turn to the analyses based on prior experience. The results are shown in **Table 3.6.3** below. Equation III in Panel A refers to properties with no prior wildfire experience. An outstanding finding here is that in the absence of wildfire experience, preferences for a higher number of prescribed fires is positive, large, and highly statistically significant. For properties with no wildfire experience, marginal increase in the number of prescribed fires is associated with a price increase as large as 30.7 percent for the first year prior to sale date. As expected, coefficients are larger for most recent fires, and we again hypothesize that this is due to the decreasing nature of risk reduction effects over time and/or availability heuristics. Coefficients are statistically significant at the five percent level or lower, and the R^2 is relatively high. Monetary impacts of prescribed fire exposure in the absence of wildfires range between 799-2761 AUD – see **Table 3.6.4** below. We believe that this large and positive preference for prescribed fires in absence of wildfire exposure is explained by the high value that households assign to risk reduction effects. Hence, it could be that households with no wildfire experience heavily rely on prescribed fires for risk reduction effects and therefore especially welcome these. Another possible explanation is that households interpret the absence of wildfires as a successful outcome of prescribed fires, and therefore value these to a greater extent than if the outcome were unsuccessful.

Interestingly, the opposite is also true: in the absence of prescribed fire experience (equation V in Panel A, **Table 3.6.3**), preferences for a higher number of wildfires is positive and highly statistically significant. However, coefficients are smaller, e.g., in the absence of prescribed fires, one additional wildfire in the first year prior to sale date is associated with a price increase of 3.4 percent. Here too coefficients are larger for most recent fires, and we again hypothesize the same reasons previously outlined. All coefficients are statistically significant at the one percent level. We could think that, in the absence of prescribed fires, wildfires should be greatly valued because of households' higher reliance on wildfires for risk reduction effects. Nevertheless, we believe that the smaller coefficients are explained by the unplanned nature of wildfires, which give rise to a higher risk of property damage and higher disamenity impacts - e.g., smoke haze, burnt vegetation, and information on the loss of wildlife and biodiversity -, compared to prescribed fires which are planned strategically to minimise these impacts.

When we restrict our sample to observations with wildfire fire experience, we get mixed results and generally statistically insignificant, with very low R^2. The same is true when we restrict our sample to observations with prescribed fire experience - see equations II and IV in Panel A of **Table 3.6.3** below. These results might be explained by the fact that - in contrast to equations III and V - the substitution in risk reduction effects between prescribed and wildfires is not clearly identifiable because experience with these two types of fires is also not clearly identifiable. For example, for equation II we know that all observations have experience with wildfires, but we do not distinguish between observations with and without prescribed fire experience. The same logic applies for equation IV. Additionally, we have lost an important number of observations by making such restrictions. The main insight we get here is that, because risk reduction effects seem to be the most important predictor of property price in our model, any sample restriction should not diminish the ability of our model to account for the aforementioned substitution effect[68].

In Panel B of **Table 3.6.3**, results are also generally mixed, statistically insignificant, and with low R^2. Therefore, we continue to confirm that households assign a higher weight to the frequency component of risk than to consequence. A notable exception is that of equation III, where the R^2 is 0.33. Results here suggest a positive preference for large prescribed fires in recent years, and a negative preference for large prescribed fires for older years (although coefficients are only statistically significant for the first and fifth years). This could simply mean that large prescribed fires exhibit larger disamenity impacts than small prescribed fires; a negative impact that is compensated with strong risk reduction effects when the fire is recent, but not when the fire is old.

Overall, the experience analysis provides three important insights. First, it strengthens our main findings from **Table 3.6.1**, suggesting that the risk reduction effect from fires is in fact the main predictor of household's preferences for both prescribed and wildfires. Second, that prescribed and wildfires are substitutes in terms of risk reduction effects, and that this substitution relationship is better identified when we restrict our sample to only one type of fire. Third, that prescribed and wildfires are not perfect substitutes due to the unplanned nature of wildfires that make them more risky

[68] For example, for equation II, all observations have wildfire experience, and some of these have prescribed fire experience, while others do not. With equation III, we found that there is a high preference for prescribed fires when there is no wildfire experience. Yet, in equation II we are dismissing this relationship by ignoring all observations without wildfire experience. Therefore, coefficients on pf_l^m are unable to capture the strong substitution effect. This is not the case for equations III because, by restricting the sample to observations with no wildfire experience, the sample is restricted to observations where the substitution effect should be stronger (and it is). The same is true for equation V.

and the planned nature of prescribed fires which are strategically planned to minimise risks. Prescribed fires are therefore substitutes of higher value.

Table 3.6.3: Experience analysis results

	Panel A number of fires				Panel B area burnt (m^2)			
Sample	wildfire experience		prescribed fire experience		wildfire experience		prescribed fire experience	
	yes	no	yes	no	yes	no	yes	no
Equation	II	III	IV	V	II	III	IV	V
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
pf_{t-1}^{t-0}	0.006	0.307***	0.012*		4.60e-09*	5.87e-08**	6.49e-09**	
	(0.005)	(0.045)	(0.006)		(2.69e-09)	(2.32e-08)	(2.69e-09)	
pf_{t-2}^{t-1}	0.012**	0.283***	0.019***		5.97e-09***	3.17e-09	5.87e-09***	
	(0.005)	(0.049)	(0.005)		(2.08e-09)	(3.43e-08)	(2.12e-09)	
pf_{t-3}^{t-2}	-0.000	0.242***	0.005		2.77e-09	5.93e-08	3.73e-09	
	(0.005)	(0.040)	(0.006)		(2.37e-09)	(6.35e-08)	(2.33e-09)	
pf_{t-4}^{t-3}	0.004	0.186***	0.009		1.60e-09	1.49e-08	2.28e-09	
	(0.006)	(0.054)	(0.006)		(2.78e-09)	(4.31e-08)	(2.79e-09)	
pf_{t-5}^{t-4}	-0.006	0.174***	-0.003		-2.03e-09	-5.69e-08**	-1.33e-09	
	(0.005)	(0.066)	(0.005)		(2.05e-09)	(2.55e-08)	(2.09e-09)	
pf_{t-6}^{t-5}	0.001	0.223**	0.007		-2.35e-09	-2.62e-08	-7.39e-10	
	(0.005)	(0.101)	(0.006)		(2.03e-09)	(4.96e-08)	(2.15e-09)	
wf_{t-1}^{t-0}	-0.002		-0.002	0.034***	-7.72e-10		-5.83e-09**	3.69e-09**
	(0.002)		(0.003)	(0.003)	(1.36e-09)		(2.29e-09)	(1.67e-09)
wf_{t-2}^{t-1}	0.004*		0.002	0.038***	1.26e-09		-4.73e-09**	3.76e-09
	(0.002)		(0.003)	(0.003)	(2.66e-09)		(2.30e-09)	(4.53e-09)
wf_{t-3}^{t-2}	-0.003		-0.004*	0.032***	-4.94e-10		-5.00e-09	-3.95e-09
	(0.002)		(0.002)	(0.003)	(1.72e-09)		(3.50e-09)	(5.08e-09)
wf_{t-4}^{t-3}	-0.002		-0.000	0.023***	-3.56e-09**		-2.45e-09	-1.28e-08***
	(0.002)		(0.003)	(0.004)	(1.57e-09)		(2.56e-09)	(4.25e-09)
wf_{t-5}^{t-4}	0.005**		0.002	0.022***	-9.07e-09***		-1.35e-08***	-7.73e-09***
	(0.002)		(0.003)	(0.004)	(2.92e-09)		(3.48e-09)	(2.81e-09)
wf_{t-6}^{t-5}	0.004*		-0.002	0.014***	-3.47e-09		-5.82e-09	-5.79e-09*

Table 3.6.3: Experience analysis results

	Panel A number of fires				Panel B area burnt (m^2)			
Sample	wildfire experience		prescribed fire experience		wildfire experience		prescribed fire experience	
	yes	no	yes	no	yes	no	yes	no
Equation	II	III	IV	V	II	III	IV	V
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
	(0.002)		(0.004)	(0.004)	(2.55e-09)		(3.63e-09)	(3.37e-09)
α	12.900***	12.870***	12.916***	12.842***	12.910***	12.890***	12.920***	12.890***
	(0.009)	(0.024)	(0.023)	(0.011)	(0.008)	(0.024)	(0.019)	(0.011)
Observations	60,846	28,573	20,347	69,072	60,844	28,575	20,347	69,072
Property IDs	53,750	26,148	18,392	60,894	53,748	26,150	18,392	60,894
R^2 within	0.057	0.348	0.065	0.115	0.058	0.333	0.078	0.097
R^2 between	0.001	0.023	0.006	0.019	0.001	0.018	0.001	0.005
R^2 overall	0.001	0.030	0.004	0.021	0.002	0.025	0.001	0.006

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6.4: Experience analysis results - Average impacts

equation	variable	exposure indicator	mean exposure	estimated coefficient[a]	average impact %[b]	average impact AUD[c]
III	pf_{t-1}^{t-0}	number of fires	0.021	0.307	0.651	2655
III	pf_{t-2}^{t-1}	number of fires	0.024	0.283	0.676	2761
III	pf_{t-3}^{t-2}	number of fires	0.022	0.242	0.526	2146
III	pf_{t-4}^{t-3}	number of fires	0.020	0.186	0.373	1522
III	pf_{t-5}^{t-4}	number of fires	0.016	0.174	0.282	1151
III	pf_{t-6}^{t-5}	number of fires	0.009	0.223	0.196	799
III	pf_{t-1}^{t-0}	area burnt	15871.380	0.0000000587	0.093	380
IV	wf_{t-1}^{t-0}	area burnt	694688.100	-0.00000000583	-0.405	-1780
IV	wf_{t-2}^{t-1}	area burnt	704377.900	-0.00000000473	-0.333	-1464
V	wf_{t-1}^{t-0}	number of fires	0.416	0.034	1.413	5900
V	wf_{t-2}^{t-1}	number of fires	0.335	0.038	1.274	5320
V	wf_{t-3}^{t-2}	number of fires	0.323	0.032	1.033	4312
V	wf_{t-4}^{t-3}	number of fires	0.306	0.023	0.703	2937
V	wf_{t-5}^{t-4}	number of fires	0.289	0.022	0.637	2659
V	wf_{t-6}^{t-5}	number of fires	0.276	0.014	0.386	1611
V	wf_{t-1}^{t-0}	area burnt	57404.380	0.00000000369	0.021	88

[a] estimated coefficients are those in **Table 3.6.3**.
[b] average impact (%) is calculated as: (mean exposure) x (estimated coefficient) x 100
[c] average impact (AUD) is calculated as (average impact (%))/100*(mean price), where mean sale price is 422,486.8 AUD.

3.7 DISCUSSION

In the previous section we used a HPM with property FE and found that prescribed fires are in general valued positively by households, with risk reduction effects dominating over disamenity impacts, and to a greater extent for those without wildfire experience. In this section, we challenge these findings by exploring the impact of extreme events and of different modelling choices. For the impact of extreme events, we check for changes in the capitalisation of prescribed and wildfires after a major wildfire disaster. Then we investigate if our results remain robust when we employ the 'standard' HPM without property FE, and a 'hybrid' model with property FE and time-varying property attributes, to see how important time constant attributes are in the identification of our HPF.

Regarding the exploration of the impact of wildfire disasters, we do this because we believe wildfire disasters may provide households with an opportunity to update their beliefs and cause them to assess prescribed and wildfires differently thereafter. This is because low probability events, such as disasters, are more salient than milder events and are therefore easier to retrieve due to availability heuristics[69]. Indeed, extreme events can change subjective probabilities of occurrence and magnitude (Kousky, 2010). For this purpose, we use the Waroona Fire of 2016 (simply 'Waroona Fire' from this point forward) as a case study[70].

The Waroona fire sparked over night with a lightning strike south of the Dwellingup State Forest on the 5th of January of 2016, but was first detected the next morning. It burnt more than 69 thousand ha, leaving two fatalities, 181 dwelling destroyed, and more than three thousand ha of forest plantations were lost (Government of Western Australia, 2016). Importantly, we choose to study the Waroona Fire because it is the wildfire disaster with most dwellings destroyed over our study period, and because of the media attention generated by this event – see **Table 3.7.1** below for a short description of wildfires in WA that were afterwards the subject of a special inquiry.

As suggested earlier, large wildfires, as that of Waroona, are likely accompanied by higher risk of property damage and high disamenity impacts. Increased risk perceptions may be subjectively amplified by media coverage – as would suggest Kasperson et al. (1988)'s social amplification of risk theory, i.e., the process through which public response may be amplified by, for example, the media as a social

[69] As discussed in the **Methodology** section, availability heuristics may increase risk perception of wildfires but may also have the opposite effect if households are knowledgeable of the risk reduction effects (as our findings in the previous section suggest they are).

[70] The Special Inquiry into the 2016 Waroona Fire reports that, for a range of reasons, the annual burning targets were not met almost every year over the last 12 years prior to the fire, and that prescribed fires remain to be the "best practice to reduce the severity of fire over broad forest landscapes" (Government of Western Australia, 2016, p. 91). Hence, we think it is possible that, after the fire, households may have a higher demand for prescribed burning.

institution. Therefore, it is sensible to expect a change in preference for wildfires, especially for those with higher area burnt. It is also sensible to expect a higher demand for prescribed fires in an effort to prevent uncontrollable wildfires.

Our results - see **Table 3.7.2** below– suggest two things. First, and most importantly, that splitting the sample before-and-after the Waroona Fire worsens the goodness of fit of our model , given that the R^2 is lower than in **Table 3.6.1** above.

Second, that after the Waroona Fire, households exhibit a negative preference for both the number of wildfires and the area burnt by these. Moreover, coefficients on area burnt by wildfires are statistically more significant than for number of fires, and also larger than those in **Table 3.6.1**. This suggests that, after the Waroona Fire, households give importance to both frequency and consequence components of risk and that disamenity impacts dominate over risk reduction effects. Every additional fire is associated with a price decrease of 1.1-1.8 percent between the first five years prior to sale date. And every additional km^2 of area burnt by wildfires is associated with a price decrease of 2.1-5.6 percent between the first six years prior to sale date. However, we find it strange that the negative impact of area burnt by wildfires does not follow a declining trend over time, and we notice that the coefficients on the number of wildfires are sometimes of low statistical significance.

It is also disconcerting that preference for prescribed fires is not always, nor generally, positive and statistically significant, especially after the Waroona Fire, when one would expect higher demand for prescribed fires.

Table 3.7.1: Bushfire Inquiries of WA

Inquiry number	Inquiry Title	Fire date[a]	Dwellings destroyed[a]	Dwellings damaged[a]	Fatalities[a]	Area burnt (ha)[a]
INQ200	A Shared Responsibility: The Report of the Perth Hills Bushfire February 2011 Review	Jan 2011	71	39	0	n.a.
INQ201	Major Incident Review: Lake Clifton, Red Hill and Roleystone Fires June 2011	Jan 2011	81	119	0	> 3,015
INQ203	Post Incident Analysis for Blackwood Fire 11 (WA)	Nov 2011	0	"several"	0	50,000
INQ223	Appreciating the Risk: Report of the Special Inquiry into the November 2011 Margaret River Bushfire (WA)	Nov 2011	0	32	n.a.	3,400
INQ226	Post Incident Analysis Blackwood Fire 8 (WA)	Nov 2011	0	45	3	2,000
INQ225	Major Incidence Review Black Cat Creek Fire (WA)	Oct 2012	1	n.a.	1	> 1,300
INQ265	Parkerville Stoneville Mt Helena Bushfire Review (WA)	Jan 2014	57	6	0	386
INQ277	Major Incident Review of the Lower Hotham and O'Sullivan fires DFES (WA)	Jan 2015	2	4	0	150,373
INQ290	Major Incident Review of the Esperance District Fires DFES (WA)	Nov 2015	16	2	4	310,000
INQ291	Waroona Fire Special Inquiry (WA)	Jan 2016	181	n.a.	2	69,165

[a] As described in the inquiry report.
Source: BNHCRC (2023).

Table 3.7.2: Before and after Waroona Fire of 2016

	Panel A number of fires		Panel B area burnt (m²)	
Equation	I	I	I	I
Sample	Before	After	Before	After
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
pf_{t-1}^{t-0}	0.018*	-0.030*	9.08e-09**	1.36e-08
	(0.011)	(0.017)	(3.96e-09)	(8.55e-09)
pf_{t-2}^{t-1}	0.012	0.009	3.98e-09	6.37e-09
	(0.009)	(0.015)	(3.37e-09)	(7.21e-09)
pf_{t-3}^{t-2}	0.008	-0.022	2.57e-09	-1.44e-08
	(0.010)	(0.018)	(2.70e-09)	(1.36e-08)
pf_{t-4}^{t-3}	0.010	-0.014	8.94e-09**	1.75e-08
	(0.008)	(0.014)	(3.49e-09)	(1.36e-08)
pf_{t-5}^{t-4}	-0.001	-0.009	2.50e-10	5.29e-09
	(0.008)	(0.017)	(3.16e-09)	(6.67e-09)
pf_{t-6}^{t-5}	0.023***	-0.015	5.21e-09*	-4.06e-09
	(0.007)	(0.018)	(3.02e-09)	(6.47e-09)
wf_{t-1}^{t-0}	0.005*	-0.012**	3.15e-09	-4.52e-08***
	(0.003)	(0.005)	(2.39e-09)	(8.34e-09)
wf_{t-2}^{t-1}	0.010**	-0.011*	-5.72e-09	-2.21e-08***
	(0.004)	(0.006)	(3.91e-09)	(7.32e-09)
wf_{t-3}^{t-2}	-0.002	-0.018***	9.39e-10	-5.58e-08***
	(0.004)	(0.006)	(2.44e-09)	(8.86e-09)
wf_{t-4}^{t-3}	-0.001	-0.014*	-8.17e-10	-2.16e-08***
	(0.004)	(0.008)	(2.21e-09)	(6.21e-09)
wf_{t-5}^{t-4}	-0.001	-0.012*	-1.10e-09	-2.73e-08***
	(0.004)	(0.006)	(3.36e-09)	(5.54e-09)
wf_{t-6}^{t-5}	-0.003	-0.007	7.90e-10	-2.14e-08***
	(0.004)	(0.007)	(2.72e-09)	(7.25e-09)
α	12.840***	12.800***	12.850***	12.780***
	(0.012)	(0.021)	(0.010)	(0.018)
Observations	57,907	31,512	57,907	31,512
Property IDs	53,773	30,732	53,773	30,732
R2 within	0.0436	0.0320	0.0412	0.0438
R2 between	0.0004	0.0042	0.0007	0.0010
R2 overall	0.0002	0.0041	0.0004	0.0010

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Now we examine our choice to include property FE. When using property FE, we assume that all property characteristics other than fire history remain unchanged throughout our study period, e.g., a property sold in 2010 and 2015 is assumed to have the same attributes. This might of course, be false, leading us to omitted variable bias. Another potential problem of using property FE is that we rely on a subsample of properties, specifically those that have more than one sale. In our dataset, 21902 observations correspond to sales of properties sold more than once, and the number of unique properties sold more than once is 10571 (of which 9845, 692, and 34 unique properties were sold two, three, and four times, respectively). This raises the question on whether this sample of 10571 properties is representative of the population.

To deal with the issue of time-varying property attributes, we experiment with a 'hybrid' HPM, i.e., one where we include property FE and all time-varying property attributes, as that suggested by Case & Quigley (1991) and Shiller (1993). Most of these time-varying attributes correspond to the property's structural characteristics, such as area size, and whether or not the property has a study room, garage, number of parking spaces, etc. This suggests that some properties in our dataset were extended or redesigned between sales. Additionally, given the introduction of bushfire prone area (BPA)[71] maps in late 2015, a subset of our sample experiences a change in BPA designation, i.e., some of the properties sold before and after the introduction of BPA maps are located in newly designated BPAs[72]. The first two columns in **Table 3.7.3** below present our results for this hybrid model. Unsurprisingly, the R^2 within are now much larger than in **Table 3.6.1**, i.e., 0.15 versus 0.08 for the model using number of fires as exposure indicator, and 0.14 versus 0.07 for the model using area burnt. When we use number of fires as exposure indicator, our findings are similar as in **Table 3.6.1**: i) recent prescribed fires are positively valued by households, and ii) wildfires are also positively valued and have long-lasting impacts. However, we do note that, for some time periods, coefficients for prescribed fires change sign and lose significance.

[71] A BPA is an area defined as being "subject to or likely to be subject to bushfire attack" (DFES, p. 2).
[72] BPA maps are updated yearly, and the first designation took place on the 8th of December 2015. All properties sold before and after this first designation date experience a change in our BPA dummy variable. Subsequent designations present little change, so only a few observations experience a change in our BPA dummy.

To deal with the issue of sample representativeness, we experiment with the standard HPM, where all observed time-constant and time-varying attributes, but property FE are excluded. Amongst other observable attributes, we include those that are indicative of wildfire risk, such as distance to the forest, and whether the property is within a designated bushfire prone area (BPA) or an LMZ. We also include attributes that may attenuate wildfire risk, such as distance to nearest fire station and to a sandy coastline or public beach (as last resort means of evacuation) – see **Table 3.9.1** in **the Appendix** for the full list of attributes included. Despite including a long list of observable attributes, results for the standard HPM contradict our main findings – see **Table 3.7.3** below. In particular, when looking at the results using number of fires as exposure indicator, we see that preference for prescribed fires is negative for most time periods, and preference for recent wildfires is positive but negative for older wildfires. When using area burnt as exposure indicator, preference for prescribed fires is also negative, but all coefficients for wildfires are statistically insignificant. We find it hard to make sense of these results, as it is not sensible that residents value prescribed fires negatively whilst valuing wildfires positively. This not only contradicts our main findings, but also findings of previous studies. Hence, we believe that – despite the substantially higher R^2 in the standard HPM – this is a confirmation that properties in our sample have unobservable attributes that influence the preference for prescribed fires. For instance, flammability of the property and of properties immediately nearby is unobservable. For example, during the Waroona Fire, several houses burnt were made of timber, and this contributed to the spread of the fire by ember attack across houses (Government of Western Australia, 2016). We also do not have information on the slope of the terrain to determine how accessible this is for firefighters or how easily a fire can spread. Nor do we have information on wildfire insurance premiums. Property FE would control for these unobservable attributes, as long as these do not vary across our study period.

Table 3.7.3: Alternative models

	Hybrid HPM		**Standard HPM**	
	Panel A number of fires	Panel B area burnt (m²)	Panel A number of fires	Panel B area burnt (m²)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
pf_{t-1}^{t-0}	0.00791	4.12e-09	-0.00706**	-9.84e-09***
	(0.00534)	(2.61e-09)	(0.00317)	(1.34e-09)
pf_{t-2}^{t-1}	0.0176***	3.68e-09*	0.00807**	-1.87e-09
	(0.00465)	(2.11e-09)	(0.00336)	(1.36e-09)
pf_{t-3}^{t-2}	0.0151***	3.05e-09	-0.00383	-5.32e-09***
	(0.00501)	(2.32e-09)	(0.00353)	(1.34e-09)
pf_{t-4}^{t-3}	0.00736	-1.41e-09	-0.00834**	-3.84e-09***
	(0.00495)	(2.59e-09)	(0.00353)	(1.32e-09)
pf_{t-5}^{t-4}	-0.00548	-1.63e-09	-0.0219***	-6.01e-09***
	(0.00502)	(2.10e-09)	(0.00350)	(1.42e-09)
pf_{t-6}^{t-5}	-0.00207	-3.48e-09	-0.0236***	-6.20e-09***
	(0.00537)	(2.56e-09)	(0.00357)	(1.32e-09)
wf_{t-1}^{t-0}	0.0106***	1.13e-09	0.00829***	-6.39e-10
	(0.00178)	(1.28e-09)	(0.00116)	(1.20e-09)
wf_{t-2}^{t-1}	0.0138***	4.13e-09*	0.00835***	1.70e-09
	(0.00192)	(2.43e-09)	(0.00131)	(1.22e-09)
wf_{t-3}^{t-2}	0.0103***	2.16e-09	0.000199	3.73e-10
	(0.00180)	(3.15e-09)	(0.00130)	(1.47e-09)
wf_{t-4}^{t-3}	0.00948***	-1.83e-09	0.00133	1.96e-09
	(0.00206)	(2.07e-09)	(0.00137)	(1.47e-09)
wf_{t-5}^{t-4}	0.00590***	-1.12e-08***	-0.00639***	-5.56e-10
	(0.00209)	(3.39e-09)	(0.00137)	(1.65e-09)
wf_{t-6}^{t-5}	0.00176	-7.29e-09*	-0.0157***	-1.17e-09
	(0.00249)	(3.84e-09)	(0.00144)	(1.74e-09)
α	12.63***	12.66***	12.160***	12.150***
	(0.0531)	(0.0531)	(0.0233)	(0.0233)
Observations	65,848	65,848	65,848	65,848
Property IDs	58,874	58,874		
R^2 within	0.1521	0.1414		
R^2 between	0.0694	0.1195		
R^2 overall	0.0741	0.1250	0.472	0.471
Property FE	Yes	Yes	No	No

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Note: we lose observations due to missing values on structural attributes (area size, number of parking spaces ('Parking'), and number of bathrooms ('Baths')).

Our findings of a positive preference using property FE and the hybrid models align with previous findings in the literature that suggest lower forest density is preferred in the immediate vicinity of the property (Hjerpe, et al., 2016) and that there is a positive WTP for fuel treatment programs, e.g., Loomis et al. (2004), Loomis et al. (2009), Gonzalez-Caban et al. (2007) and Kaval et al. (2007).

3.8 CONCLUSIONS

In this paper, we study households' preferences for wildfire safety by modelling property price as a function of risk and amenity values, which are in turn, explained by exposure to prescribed and wildfires prior to sale date. We further propose that both prescribed and wildfires can be incorporated into risk and amenity value judgements by accounting for their frequency or consequence. Hence, we present two versions of our model. The first version looks at frequency, accounted for by number of fires; and the second version looks at consequence, accounted for by area burnt. By limiting exposure to a 5 km radius from the property's latitude and longitude, we expect to account for local preferences only. Additionally, limiting exposure to the first six years prior to sale date, we align with field and academic evidence on the effectiveness of prescribed fires over time.

Contrary to the opposition of some residents and natural scientists to prescribed burning featured in the media, we find that exposure to prescribed fires is a desirable attribute for households in WA, especially the most recent ones. Importantly, this is after controlling for exposure to wildfires. The positive preference suggests that the transient disamenity impacts from smoke, haze, road closures, and concerns around fire escapes, and the longer-term concerns about wildlife and biodiversity are overridden by the risk reduction effects, as perceived by households. The fact that households have a positive preference for recent prescribed fires in particular is consistent with the decreasing nature of risk reduction effects over time, i.e., as fuel age increases, so does wildfire risk; and also consistent with availability heuristics, as more recent events are easier to retrieve than older ones.

Furthermore, our experience analysis reveals that properties without wildfire exposure are associated with a large and statistically significant price mark-up when exposed to prescribed fires. This is an important finding, as it strongly suggests that, in a region prone to wildfires, as that of WA, prescribed and wildfires are substitutes in terms of risk reduction effects, i.e., in the absence of wildfires, households heavily rely on prescribed fires for risk reduction effects. As can be expected, prescribed fires are better valued than wildfires, which entail higher risk to property damage and higher disamenity impacts.

Importantly, we find that households pay more attention to the frequency component of risk, rather than consequence, as our results are generally stronger when we use the number of fires as exposure indicator rather than area burnt, i.e., when using number of fires as exposure indicator, coefficients are generally more statistically significant and estimated monetary impacts are generally larger. This finding aligns with that of Brenkert-Smith, et al. (2013)'s survey analysis on the social amplification of wildfire risk in Colorado, US, where the authors find evidence that information sources and social interaction can alter perceived frequency of wildfires, but not perceived consequence.

Additionally, our findings seem to suggest that the use of property FE is essential to account for unobservable time-constant attributes that have an effect on safety preferences, such as property's flammability and terrain slope, and property-level data on insurance premiums.

Our work could be expanded by studying the heterogeneity in safety preferences across households. For instance, given the strong historic link between indigenous Australians and prescribed burning, it would be interesting to explore whether or not ethnicity plays a role in acceptance or rejection of prescribed burning. We also think it would be worthy to investigate the heterogeneity in safety preferences within the 5 km radius, i.e., to replicate our model using several distance intervals (e.g., 0.5, 1, 2, and 5 km), to identify the spatial dynamics between risk perception and disamenity impacts, e.g., to see if risk reduction effects continue to dominate over disamenity impacts even when very close to the burn scar. Additionally, given that fire size has an impact on risk and amenity levels, we believe our research could benefit from classifying fires according to size, e.g., from very small to very large. This would let us examine heterogeneous preferences for the scale of prescribed and wildfires.

3.9 APPENDIX

Table 3.9.1: Alternative models

	Without property FE and all attributes		With property FE and all time-varying attributes	
	Panel A number of fires	Panel B area burnt (m²)	Panel A number of fires	Panel B area burnt (m²)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
spring	-0.00472	-0.00458		
	(0.00356)	(0.00356)		
autumn	-0.00509	-0.00516		
	(0.00351)	(0.00352)		
winter	-0.0144***	-0.0144***		
	(0.00357)	(0.00357)		
pf_{t-1}^{t-0}	-0.00706**	-9.84e-09***	0.00791	4.12e-09
	(0.00317)	(1.34e-09)	(0.00534)	(2.61e-09)
pf_{t-2}^{t-1}	0.00807**	-1.87e-09	0.0176***	3.68e-09*
	(0.00336)	(1.36e-09)	(0.00465)	(2.11e-09)
pf_{t-3}^{t-2}	-0.00383	-5.32e-09***	0.0151***	3.05e-09
	(0.00353)	(1.34e-09)	(0.00501)	(2.32e-09)
pf_{t-4}^{t-3}	-0.00834**	-3.84e-09***	0.00736	-1.41e-09
	(0.00353)	(1.32e-09)	(0.00495)	(2.59e-09)
pf_{t-5}^{t-4}	-0.0219***	-6.01e-09***	-0.00548	-1.63e-09
	(0.00350)	(1.42e-09)	(0.00502)	(2.10e-09)
pf_{t-6}^{t-5}	-0.0236***	-6.20e-09***	-0.00207	-3.48e-09
	(0.00357)	(1.32e-09)	(0.00537)	(2.56e-09)
wf_{t-1}^{t-0}	0.00829***	-6.39e-10	0.0106***	1.13e-09
	(0.00116)	(1.20e-09)	(0.00178)	(1.28e-09)
wf_{t-2}^{t-1}	0.00835***	1.70e-09	0.0138***	4.13e-09*
	(0.00131)	(1.22e-09)	(0.00192)	(2.43e-09)

Table 3.9.1: Alternative models

	Without property FE and all attributes		With property FE and all time-varying attributes	
	Panel A number of fires	Panel B area burnt (m^2)	Panel A number of fires	Panel B area burnt (m^2)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
wf_{t-3}^{t-2}	0.000199	3.73e-10	0.0103***	2.16e-09
	(0.00130)	(1.47e-09)	(0.00180)	(3.15e-09)
wf_{t-4}^{t-3}	0.00133	1.96e-09	0.00948***	-1.83e-09
	(0.00137)	(1.47e-09)	(0.00206)	(2.07e-09)
wf_{t-5}^{t-4}	-0.00639***	-5.56e-10	0.00590***	-1.12e-08***
	(0.00137)	(1.65e-09)	(0.00209)	(3.39e-09)
wf_{t-6}^{t-5}	-0.0157***	-1.17e-09	0.00176	-7.29e-09*
	(0.00144)	(1.74e-09)	(0.00249)	(3.84e-09)
Area (m^2)	2.97e-07	2.96e-07	4.07e-06*	2.54e-06
	(2.13e-07)	(2.12e-07)	(2.15e-06)	(2.09e-06)
Bedrooms	0.0587***	0.0583***	0.0420***	0.0428***
	(0.00623)	(0.00620)	(0.0143)	(0.0144)
Baths	0.197***	0.197***	0.0526***	0.0536***
	(0.00915)	(0.00914)	(0.0173)	(0.0174)
Parking	0.0196***	0.0193***	0.00791***	0.00835***
	(0.00125)	(0.00125)	(0.00233)	(0.00231)
HasStudy	0.103***	0.104***	0.0226***	0.0197**
	(0.00320)	(0.00320)	(0.00815)	(0.00815)
HasSeparateDining	-0.0181***	-0.0189***	-0.00731	-0.00691
	(0.00475)	(0.00476)	(0.00855)	(0.00861)
HasFamilyRoom	0.0319***	0.0320***	-0.00871	-0.0163
	(0.00528)	(0.00528)	(0.0195)	(0.0192)
HasSunroom	0.0274**	0.0274**	-0.00282	-0.00423
	(0.0110)	(0.0109)	(0.0167)	(0.0161)
HasRumpusRoom	0.0127***	0.0121***	-0.00730	-0.00765
	(0.00380)	(0.00381)	(0.00675)	(0.00671)

Table 3.9.1: Alternative models

	Without property FE and all attributes		With property FE and all time-varying attributes	
	Panel A number of fires	Panel B area burnt (m²)	Panel A number of fires	Panel B area burnt (m²)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
HasFireplace	0.0383***	0.0389***	0.0165**	0.0161**
	(0.00461)	(0.00461)	(0.00644)	(0.00638)
HasWalkInWardrobe	0.00237	0.00305	0.0142**	0.0146**
	(0.00343)	(0.00344)	(0.00586)	(0.00592)
HasCourtyard	-0.00186	-0.00115	0.00517	0.00616
	(0.00546)	(0.00547)	(0.0112)	(0.0112)
HasInternalLaundry	0.00541	0.00647	0.0229**	0.0268***
	(0.00595)	(0.00594)	(0.00931)	(0.00916)
HasHeating	0.000148	0.000601	0.00162	0.000554
	(0.00392)	(0.00392)	(0.00571)	(0.00570)
HasAirConditioning	-0.0192***	-0.0186***	0.0250***	0.0270***
	(0.00269)	(0.00269)	(0.00525)	(0.00527)
HasBalcony	0.234***	0.234***	0.0288***	0.0265**
	(0.00546)	(0.00545)	(0.0111)	(0.0111)
HasBarbeque	0.0376***	0.0368***	0.0110	0.0127
	(0.00550)	(0.00550)	(0.00984)	(0.00985)
HasPolishedTimberFloor	0.0636***	0.0627***	0.0163*	0.0150*
	(0.00569)	(0.00569)	(0.00862)	(0.00848)
HasEnsuite	0.0285***	0.0283***	0.00426	0.00389
	(0.00383)	(0.00384)	(0.00567)	(0.00568)
HasSpa	0.0755***	0.0756***	-0.0147*	-0.0175**
	(0.00502)	(0.00503)	(0.00803)	(0.00801)
HasGarage	0.0825***	0.0819***	0.0361***	0.0373***
	(0.00316)	(0.00316)	(0.0118)	(0.0119)
HasLockUpGarage	-0.0232***	-0.0238***	-0.0221***	-0.0219***
	(0.00443)	(0.00443)	(0.00794)	(0.00795)

Table 3.9.1: Alternative models

	Without property FE and all attributes		With property FE and all time-varying attributes	
	Panel A number of fires	Panel B area burnt (m^2)	Panel A number of fires	Panel B area burnt (m^2)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
HasPool	0.124***	0.125***	-0.00856	-0.00942
	(0.00465)	(0.00465)	(0.0171)	(0.0172)
HasTennisCourt	0.0648	0.0615	-0.0107	-0.0126
	(0.0484)	(0.0485)	(0.0457)	(0.0463)
HasAlarm	0.0805***	0.0799***	0.0178***	0.0195***
	(0.00523)	(0.00523)	(0.00680)	(0.00681)
distance to forest	5.64e-06***	5.62e-06***		
	(8.19e-07)	(8.38e-07)		
distance to sandy coastline	-4.71e-07***	-4.63e-07***		
	(2.62e-08)	(2.62e-08)		
distance to wetland	-1.43e-06***	-1.41e-06***		
	(7.96e-08)	(7.92e-08)		
distance to beach	1.81e-07***	1.72e-07***		
	(1.94e-08)	(1.94e-08)		
BPA	0.132***	0.134***	0.0506***	0.0589***
	(0.00472)	(0.00472)	(0.00962)	(0.00968)
LMZ-A	0.156***	0.159***		
	(0.00543)	(0.00537)		
LMZ-B	0.280***	0.285***		
	(0.0196)	(0.0195)		
LMZ-C	0.212***	0.301***		
	(0.0508)	(0.0539)		
distance to fire station	8.33e-06***	8.16e-06***		
	(1.33e-06)	(1.33e-06)		
distance to bus stop	-7.47e-07***	-7.47e-07***		
	(2.97e-08)	(3.78e-08)		

Table 3.9.1: Alternative models

	Without property FE and all attributes		With property FE and all time-varying attributes	
	Panel A number of fires	Panel B area burnt (m^2)	Panel A number of fires	Panel B area burnt (m^2)
Equation	I	I	I	I
VARIABLES	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
distance to train stop	2.47e-07*	2.12e-07*		
	(1.29e-07)	(1.29e-07)		
distance to Perth	8.29e-08	1.24e-07		
	(1.29e-07)	(1.29e-07)		
urban	-0.0921***	-0.0921***		
	(0.00333)	(0.00332)		
α	12.160***	12.150***	12.63***	12.66***
	(0.0233)	(0.0233)	(0.0531)	(0.0531)
Observations	65,848	65,848	65,848	65,848
R^2	0.472	0.471	0.0741	0.1250
Property FE	No	No	Yes	Yes
Fiscal year FE	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

CONCLUSIONS

Wildfires can have devastating consequences on ecosystems, biodiversity conservation and people's welfare and wellbeing. With climate and land-use change, wildfires are becoming more frequent and intense, and communities are increasingly coexisting with wildfire risk (UNEP, 2022). It is in this context that we wonder if people update their safety preferences and change behaviour in response to the risk of wildfires. We look into this by identifying changes in the sale price of residential properties, as an indicator of people's decisions on where to live, presumably one of the most important decisions one can ever make. Specifically, we use the HPM and focus our study on WA, a region of high biodiversity importance and frequently affected by wildfires but also frequently overlooked in the study of market revealed safety preferences, as opposed to wildfire-prone regions in the USA. To implement the HPM, we combine vector-based GIS data for structural, neighbourhood, and environmental attributes of properties sold between 2010 and 2019, along with their sale prices.

In **CHAPTER 1**, we implement a DD approach to study the impact of a wildfire disaster, the Waroona Fire of 2016, on near-miss households, which are defined by two different treatments: distance to the burn scar and receiving warnings during the fire. Not all households near the burn scar received warnings, making the near-miss experience different across households. We find that properties within 5 km from the burn scar experienced a price mark-up of approximately 8%, suggesting that the near-miss effect is driven by a risk reduction effect that dominates over disamenity impacts. On the other hand, those that received emergency warning alerts during the fire event experienced a price discount of approximately 6%, suggesting that warnings are effective in triggering vulnerability feelings. Our results confirm that the near-miss effect is multidimensional and not reduced to a proximity effect.

In **CHAPTER 2**, we investigate whether households update their safety preferences when introduced and exposed to BPA maps, i.e., maps that identify areas subject to, or likely to be subject to, wildfire risk, and also subject to more stringent development planning and building regulations affecting new builds. Given that these maps define a clear cut-off point that divides treated and control areas, we implement a sharp RDD where the score is defined by the distance between the property and the BPA boundary. After several robustness checks, we find that properties within BPAs experience a price discount of approximately 4%, suggesting that the mapping policy is effective in shifting housing preferences away from risky areas, and that this shift is prompted by an increased risk perception rather than by pre-determined risk perception or the more stringent planning and building regulations. This suggests, on one hand, that wildfire risk mapping could alleviate spending on management, suppression and recovery by discouraging housing in risky areas; and on the other hand, that risky areas may attract low-income households, increasing socioeconomic inequalities.

Motivated by our findings on the first and second chapters, which suggest risk reduction benefits from past wildfires and a clear preference for living in non-BPAs, in **CHAPTER 3**, we further explore safety preferences by looking at the capitalisation of prescribed burning - a forest management practice that reduces the risk of uncontrollable fires - into property prices. After controlling for wildfire exposure, we find that properties with exposure to prescribed fires are positively associated with higher property prices. This is especially true for properties with recent exposure to prescribed fires (1.2 and 2.6% higher for fires over the first and second years prior to sale date), and even more so for properties with no wildfire experience (between 17.4 – 30.7% higher over the first six years prior to sale date), suggesting that households are aware of the risk reduction effects and their decreasing nature over time, and that risk reduction effects, dominate over any disamenity impacts, despite the strong opposition due to health and biodiversity concerns. Additionally, we find stronger results when using the number of fires - instead of area burnt - as exposure indicator, suggesting that households are more perceptive of frequency - instead of consequence – when making risk judgements.

Our findings across this thesis suggest that, in areas that coexist with wildfires, such as WA, safety preferences are strong and capitalised into the housing market, giving policy makers potential to alter people's beliefs through emergency, land zoning, and forest management services (e.g., issuing emergency warnings, risk mapping and associated regulations, and prescribed burning, respectively). Emergency, land zoning, and forest management services are then, policy tools that, through changes in property prices, can have a significant impact on wealth.

For instance, in **CHAPTER 1**, we see that emergency warnings generate a distributional impact where properties in areas that received warnings decrease in price, especially those in areas where warnings were easiest to understand, suggesting that policy makers should be careful not to issue blanket warnings and that making an effort in clear risk communication is well worthwhile. We also see that properties in proximity to the burn scar experienced a price increase, suggesting that near-miss households value the reduction in future wildfire risk despite the disamenities associated with a burnt landscape. This already suggests that policy makers should pay attention to prescribed burning, as this is an alternative that entails lower risk and disamenities.

In **CHAPTER 2**, findings suggest that the provision of spatially delineated information on wildfire risk alters safety preferences, i.e., housing preferences shift away from riskiest areas, which may be particularly beneficial to society if households are indeed underestimating wildfire risk. More stringent planning and building regulations in riskiest areas could also generate positive externalities through lowering wildfire risk and the costs of a wildfire to both one's neighbours and the state. Policy makers can therefore use risk mapping to discourage housing in areas most prone to wildfires. However, they should also be careful in their vegetation management, e.g., careful in deciding which vegetation types to prioritise in urban areas, as BPA maps are defined by the presence of BPV. Moreover, policy makers should also be mindful that BPA maps might unintentionally encourage lower income households to live in BPAs due to the lower price compared to properties in non-BPAs in the neighbourhood of the boundary.

Finally, **CHAPTER 3** clearly confirms that prescribed burning is a policy tool positively valued by affected households, and that the risk reduction effect generated by burn scars from prescribed fires is preferable to that from wildfires. The extent to which prescribed burning costs should be borne by beneficiaries remains an area of debate, and so does the right to choose to live in high wildfire risk areas.

Nevertheless, the study of wildfires is broad in that there are many empirical aspects to account for, and we have faced some limitations. Throughout the thesis, the chief limitation is the inability to disentangle wildfire risk from forest and green amenities, being that wildfire risk and amenities are both greater closest to forest and green areas.

We deal with this by taking advantage of the opposite effects that risk and amenity have on experienced utility and property prices, i.e., ceteris paribus, the higher the amenity level, the higher the utility and price; the higher is wildfire risk, the lower is utility and price. Hence, we assume that both risk and amenity attributes are factored in the price function, and that the sign of our estimated coefficient determines which attribute dominates over the other. We were also limited by having no information on property age, which is an important structural attribute; and no information on insurance premiums, which can certainly alter safety preferences. Additionally, we could have benefitted from a visit to WA and in particular Waroona, as it would have enabled us to meet fire managers, local authorities, and residents. This would have helped us get additional insights on safety preferences and forest management challenges through interviews or participation in meetings, along with research collaboration opportunities. However, the COVID-19 pandemic prevented any visit to WA, and when constraints were lifted, time was already very scarce.

For **CHAPTER 1** on the near-miss effect, the chief limitation is defining the treatment group, i.e., there is no clear identification of near-miss observations. We define near-miss observations as those which had a near-miss experience, but the identification requires a multidimensional approach that starts, but does not end, with the identification of the proximity area, i.e., the area *near* the direct-hit.

The first task is to define the extension of the proximity area from the edge of the fire burn scar, and there is no golden rule for this. We deal with it by proposing four distance bands (2, 5, 10 and 20 km) and implementing a DD approach.

The next task is to account for the fact that the near-miss experience, and therefore the near-miss area, is defined by much more than proximity, e.g., changes in wildfire risk, amenity levels, and pollution levels from smoke and ash, and being exposed to emergency warnings and a high frequency of local news; all of which can affect different subgroups of households. If we focus on risk reduction effects and the loss of forest and green amenities, proximity to the direct-hit area is key and identifiable with vector-based GIS data (although a view-shed analysis - for which we lack 3D data - could increase accuracy). Yet, every other near-miss dimension is harder to identify. For instance, to identify observations affected by emergency warnings, we read through the special inquiry, which reviews warnings issued on the first two days of the fire event only. A multidimensional approach accounts for the heterogeneity of the near-miss experience across households in favour of a better identification strategy. Nevertheless, it can lead to a small number of treated observations across some dimensions, some of which could be collinear. In addition, we would have benefitted from spatial data on the dispersion of smoke and ash, and on the frequency of related local news at the Shire level, for instance.

For **CHAPTER 2**, one limitation is the inability to distinguish properties that were affected by the more stringent regulations from those that were not – as more stringent planning and building regulations affect properties that undergo building work, as well as new builds. We deal with this by assuming that repeat sales resold after the BPA map introduction are not affected by the change in regulation, whereas unique sales might be; and then we confirm that confidence intervals of coefficients on the impact of the BPA for these two groups overlap, suggesting that the drop in property prices within BPAs is not regulation driven. Needless to say, this is a weak fix, as the repeat-sale group might be affected by extensive building work and the unique-sale group may contain a large proportion of old and unaltered properties. Another limitation is that we do not have information on insurance premiums, and it could be that the price discount for properties within BPAs reflects a lower demand due to an expectation of higher insurance premiums, as suggested in de Ceglie (2015)[73].

For **CHAPTER 3**, the main limitation is that we cannot claim for causal impacts, as we could not carry out a causal-impact evaluation approach because it was not appropriate for our purpose, i.e., there is no particular event or program of interest that would generate a change in property price, but only a degree of exposure to wild and prescribed fires that would generate a difference in property price between observations. A particular challenge was that we relied heavily on conversations with experts to fully understand the terminology and recording procedure of the fire history dataset - which we initially found confusing and contradictory in some instances - to be then able to compile our own dataset. We would have also benefitted from having access to spatial data on fuel age, i.e., years since last burn, and forest density across our study period, as it more accurately represents wildfire risk and forest and green amenities.

If not limited by time constraints, we would have liked to extend our research as follows. First, by incorporating changes in air and water pollution from smoke and ash as a near-miss dimension of the Waroona Fire. Although a transient impact, we predict it could affect the housing market while the recovery process takes place. Second, by undertaking an impact event study for news sentiment analysis on the Waroona Fire,

[73] We have not found evidence of higher insurance premiums after the introduction of BPA maps and within our study period. However, it is likely that cost of home insurance is considered by households when deciding where to live. For instance, recent news articles suggest that households should consider the potentially higher cost of rebuilding in BPAs when deciding the insured amount (Bristow, 2023). On the other hand, it is also suggested that insurance premiums in BPAs are now so expensive that many households simply decide not to get insured at all (Libatique (2023)), implying that insurance premiums in BPAs have become irrelevant.

differentiating between international, national, and local media, to better understand how risk perceptions are amplified in society. Third, by complementing our research with a stated preference approach. One reason for this is to get WTP estimates on risk reduction effects and forest and green amenities, as we cannot disentangle risk reduction and disamenity impacts with our current approach, and it would be interesting to confirm that households expressly state higher valuations for risk reduction effects than for amenity values. Another reason for this is to check if stated and market revealed preferences are aligned, and further study the reasons for misalignments, if any, i.e., are people's preferences not being capitalised into the housing market? If so, why? Stated preferences can also serve as robustness checks for our results if we believe the identification strategy is not as strong as we would like, as is the case for **CHAPTER 3** on the capitalisation of prescribed burning into property prices. Fourth, by incorporating data on ethnicity in order to understand cultural differences in the preferences for prescribed burning, particularly between indigenous and non-indigenous Australians, given that the former have a long history on prescribed burning practice.

Amid a warming climate and land-use change, devastating news on wildfires will only become more frequent, including in unexpected areas (e.g., the Arctic). For this reason, we believe much more research is needed on identifying misperceptions on risk, tools for correction, and households' preferences for forest management practices - as prescribed burning -, along with an analysis on the sustainability of the practice as climate conditions for its implementation worsen.

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