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Analysis

Climate change and its impact on home insurance uptake in Australia ☆

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ABSTRACT

Climate change is impacting the frequency and severity of physical risks such as wildfire, flood, cyclone and extreme precipitation. This is changing both the costs and benefits of home insurance purchase for households—leading to uncertainty about future insurance uptake rates under climate change. We use disaggregated data for Australia on the likelihood of climate hazards, and household panel data, to model the relationship between insurance uptake and exposure to climate physical risks. This model is then used to project insurance purchase out to 2100 under three climate scenarios. We find that exposure to climate risks does influence the likelihood of purchasing insurance. While for most hazards higher risk reduces the likelihood of purchase, there are exceptions, and the relationship is often complex. Projections from our model indicate that insurance coverage is likely to decline relatively modestly, by around one percentage point across Australia from 2000 to 2100 as a result of climate change. However, we find there is significant variation across regions.

1. Introduction

Changes in the climate are having far-reaching impacts across the globe. In recent years there has been growing awareness of the physical manifestations of climate change. Changes in frequency and intensity of extreme weather – such as storms, wildfires, heatwaves, heavy rain, and floods – are challenging existing systems, disrupting many communities, and requiring the adoption of mitigating and adaptive measures to address the challenges of climate change (IPCC, 2023).

Insurance is a key mediating factor in the relationship between extreme weather, climate change, and its economic and social impact. Home building and contents insurance in particular are important in reducing the negative impacts on households from extreme climate events. Insurance limits households' financial losses and assists with rebuilding and recovery after a disaster. It also mitigates the exposure that local and national governments have to the costs of reconstruction after disasters (ACCC, 2020). However, there are growing concerns about the availability and affordability of insurance as climate change worsens for local communities (Tesselaar et al., 2020)

Australia, which is our focus, is by some measures one of the countries most exposed to the physical effects of climate change (XDI, 2023). A recent report by the Climate Council – a climate advocacy group – concluded that, "Across Australia approximately 520,940 properties, or one in every 25, will be 'high risk' and uninsurable [by 2030]" (Climate Council of Australia, 2022). Indeed, many of the prospective concerns around the cost and availability of insurance appear to be coming to fruition. A recent investigation of the cost of building and contents insurance in Australia indicated significant rises for many (CHOICE, 2023; Actuaries Institute, 2023). However, the Insurance Council of Australia (Insurance Council of Australia, 2023) notes that insurance remains broadly available across Australia; "At present there is no area of Australia that is uninsurable, although there are some locations and industries where there are clearly affordability and availability constraints".

Home insurance plays a key role in financial stability. In Australia, borrowers with a mortgage are required by lenders to have home-building insurance. The absence of insurance for disaster-hit homes poses a credit risk to banks—a borrower whose home has been severely damaged may move into negative equity and be more likely to default. Even if the likelihood of default does not change, the reduced value of damaged homes exposes the lender to a greater chance of loss. In a recent climate risk stress test run by Australia's prudential banking

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regulator, the rate of under-insurance and non-insurance of mortgage borrowers was a key focus (APRA, 2022).

Unsurprisingly, concern about the availability and affordability of home insurance in the context of climate change goes well beyond Australia. For example, Hill (2023) notes similar challenges in the US to those outlined above for Australia. The Bank of England in the UK (Bank of England, 2020), Canadian insurers (Insurance Institute, 2020) and the European Central Bank (European Central Bank, 2023), all note the important role insurance plays in mitigating disasters for households and in the distribution of risk within the financial system. There is also concern in the developing world about exposure to climate risks relative to insurance coverage (Edwards and Davis, 2012). However, there is limited existing understanding of how climatic factors impact insurance uptake and hence what the longer-term implications for insurance coverage are likely to be.

Our focus in this study is on how insurance coverage is likely to be impacted by climate change. We use data on the likelihood of physical risk events for wildfire, cyclone, flood, and extreme precipitation. This data is available annually from 1980 to 2100 for all of Australia's postcodes. We merge this with household-level panel information on home contents insurance purchase from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. This enables us to relate insurance uptake to a household's characteristics and their vulnerability to climate hazards. We address two main questions.

First, we investigate the extent to which climate risks are drivers of insurance uptake in Australia. Using the merged household panel and climate risk data we model the relationship between insurance uptake and climate risks. In identifying this relationship, we also control for a range of household characteristics such as wealth, income, age, ownership status, gender, and risk aversion.

Second, we explore how insurance uptake is likely to evolve as the climate changes. We use our model of insurance uptake, and projections of the likelihood of climate hazards out to 2100, to estimate the effects of climate change on insurance uptake over this period.

We find that climate hazard exposures are strong predictors of the likelihood of having home contents insurance even after controlling for household characteristics. The four climate hazards we examine have differential impacts on insurance uptake. A higher risk of flood and extreme precipitation reduces the likelihood of insurance purchase though for extreme precipitation the impact is non-linear. In the case of cyclone, we find that increases in risk from a low level leads to a rise in the likelihood of insurance purchase whereas for higher cyclone risk levels there is limited impact. Exposure to wildfire risks has little impact on insurance uptake. These results show the diversity and complexity of the relationship between climate hazards and insurance uptake and the value of using non-linear models to accurately reflect these. We also find that household characteristics are significant predictors of insurance purchase. Households that are more likely to purchase insurance are those with an older female household head who is employed, have higher income and wealth, are homeowners as opposed to renters, have a larger house, and are risk averse.

Our insurance model is used to project the national rate of insurance uptake under three different climate scenarios within the Shared Socioeconomic Pathways (SSP) framework (Riahi et al., 2017). The non-climate characteristics of the model are held fixed and the model is used to predict the insurance uptake rate over the period from 2000 to 2100. Under the most severe of the climate scenarios, where temperature is expected to rise by 4.4°C by 2100 (IPCC, 2021), the national results indicate a decline of around one percentage point in insurance uptake from their current levels where around three-quarters of households have coverage. In the middle scenario (+2.7°C by 2100) there is a slight decline in insurance coverage, while in the more optimistic scenario (+1.8°C by 2100) there is a very small rise in insurance uptake. Importantly, we find larger and more diverse changes at the sub-national level. Some states are projected to see falls in insurance uptake of up to 3 percentage points in the most severe scenario while others could see rises. These results depend upon the local climate risk exposures and how they are expected to evolve in the future. One caveat to our results is the high levels of modelling uncertainty around future projections of climate risks at the local level.

In the next section, we survey the relevant literature. In Section 3 we outline the Australian household panel and climate physical risk data used in the study. Section 4 outlines our methodology. In Section 5 we discuss our results while Section 6 concludes.

2. Relevant literature

This study contributes to and draws upon several streams of the literature related to modelling insurance uptake, natural disasters and their impacts, and the impact of climate change on insurance.

First to models of insurance uptake. A range of papers have explored the drivers of insurance purchase. Atreya et al. (2015) found that insurance purchase is relatively price inelastic and that those with higher education, and who are older, are more likely to purchase insurance. Bradt et al. (2021) model the rate of flood insurance uptake at the census tract level based on education, income, age, and ownership status. They found a surprising degree of heterogeneity in insurance take-up between areas that were observably very similar. This heterogeneity and complexity of the insurance purchase decision was also emphasized by Booth and Kendal (2020). They explored the relationship between underinsurance and socioeconomic disadvantage and found a complex mapping that does not directly link the two. Importantly, these models have not comprehensively examined the relationship between climate risks and insurance. Though Atreya et al. (2015) found that being in a flood plain is positively associated with insurance purchase. Bradt et al. (2021) proxied for the risk of flood in an area by including the proportion of the census tract covered by water. They found a positive association between this variable and insurance uptake. Our study will add to the evidence base by explicitly examining the role of climate risks in insurance uptake.

A second stream of the literature examines the economic and social effects of natural disasters on households. Home insurance plays a key role in mediating these impacts. Johar et al. (2022) examine the economic impacts of natural disasters in Australia using household panel data. They investigate how having your home damaged by a natural disaster impacts individuals. They find some impact on financial hardship but, interestingly, little impact on employment status or income. In a similar vein, Frijters et al. (2023) focuses on self-assessed well-being after disasters. They find relatively modest impacts in the weeks following a disaster and that these diminish relatively quickly. However, Berlemann and Eurich (2021) note significant differences in individual well-being based on the assessed risk of being effected by a natural disaster. There has been a range of work looking at Hurricane Katrina in the US. This was a severe hurricane that struck New Orleans in 2005 and caused the death of close to 2000 people and over $100 billion in damages. Deryugina et al. (2018) use tax return data and find surprisingly small and transitory effects on impacted peoples' employment and income from Hurricane Katrina. Gallagher and Hartley (2017) look at Katrina's impact on household finances. They find relatively modest effects with rises in delinquency and credit card borrowing being relatively short-lived. Interestingly, mortgage balances decline post-flood. This is likely the result of insurance payouts being used to pay down mortgages rather than rebuild.

Finally, there is longstanding and growing interest in how insurance is impacted by disasters and how it will evolve in the context of climate change. Mills (2007), Botzen et al. (2010) and Botzen and Van Den Bergh (2012) note that climate change may provide opportunities to insurers. If disasters occur with higher frequency and severity this may increase demand for insurance. Though Hudson et al. (2019) estimates that flood insurance premiums could double by 2055 in the absence of mitigation action by households. They emphasize the need to link the insurance premium with the risk and not to cross-subsidize between

high- and low-risk households. Moreover, they advocate linking the insurance premium to risk mitigation to incentivize adaptation. Gallagher (2014) look at insurance take-up in the US after floods and find a significant spike immediately after an event. However, the insurance rate reverts to baseline relatively quickly. Osberghaus, Daniel (2017) finds an increase in mitigation efforts following floods in Germany. Bourdeau-Brien and Kryzanowski (2020) find that natural disasters lead to increased risk aversion amongst municipal bond investors at the local level. Others have noted that government support in the aftermath of climate events can crowd out insurance purchase (Raschky et al., 2013; Andor et al., 2020)

3. Data

There are two main datasets used in this study. We first discuss the data on climate hazards and then turn to the HILDA Survey household panel data.

3.1. Climate risk metrics

Our climate hazards data was made available by Sust Global—a leading provider of down-scaled climate physical risk metrics. We have data from 1980 to 2100. The risk metrics are based on the CMIP6 suite of global climate models.[1] These models produce outputs for the world at varying, but usually highly aggregated, global scales. Outputs from these models are combined with various observational datasets to downscale these climate simulations to sub-national levels such as postcodes (Ballard et al., 2023; Erinjippurath and Ballard, 2023; Sust Global, 2023).

The key risk metrics that we focus on are those that are related to insurance in Australia; wildfire, flood, cyclone, and extreme precipitation. The data is available at the postcode level for Australia. Postcodes are areas developed for mail delivery similar to zip codes in the US. In Australia, postcodes can vary in size both geographically and in terms of population. There are around 2600 postcodes in Australia and the average postcode has a population of around 10,000 persons. Though postcodes in urban areas are likely to be geographically smaller and have larger populations. Postcodes are a natural and commonly used level of analysis for climate physical risks. For example, the Australian Prudential Regulation Authority (APRA) – the government agency that regulates banks – undertook an analysis of climate physical risks at this geographic level (APRA, 2022).

The climate risk metrics reflect the intuitive dimensions of each hazard and are constructed based on modelled output. For wildfire, we have the geographically weighted probability across a postcode of a wildfire in a given year. The flood metric represents the average probability that the postcode will experience a flood of more than 0.5 metres. For cyclones, our metric is the probability that any part of the postcode experiences a Category 1 or higher cyclone over the year. Finally, the extreme precipitation measure is the average number of days in the year where the rainfall is 5 cm or more. To make these metrics more readily suitable and interpretable for our purposes we undertake two transformations. First, for extreme precipitation and wildfire risk we take moving averages. This is necessary in isolating the underlying climate trend rather than the volatility induced by dynamics such as El Nino and La Nina. We take a 40-year centred moving average of this variable. For wildfire risk, we take a 10-year centred moving average. Second, we standardized each variable across postcodes and time based on their mean and variance in the year 2000.

Table 1 and Fig. 1 illustrate the distribution of the climate risk metrics across the 2641 postcodes in Australia. The risk of cyclone, wildfire, and flood are relatively low for the vast majority of postcodes. However, there are a small number of postcodes facing high risk. For example, the postcode most vulnerable to cyclones has a risk 9.20 standard deviations above the average while for flood it is a whopping 20.38 standard deviations above the average. A larger proportion of postcodes face higher risks for extreme precipitation with 25% of postcodes being 0.63 standard deviations or more above the mean.

The projected climate risk metrics are key for exploring the future trajectory of insurance uptake. For most of the variables, we have data under three scenarios reflecting different Shared Socioeconomic Pathways (SSP) (Riahi et al., 2017). These are SSP126, SSP245 and SSP585. Each of the SSPs reflect different assumptions around the key drivers of long-run forecasts such as population growth, technological change, and the extent of global agreement and cooperation on reducing carbon emissions. The SSP126 scenario (known as the Green Road) envisages a relatively modest temperature rise of around 1.8 °C by 2100 and reflects global cooperation and technological adoption leading to falling CO2 emissions (IPCC, 2021). SSP245 is a middle-of-the-road scenario where there is some effort to mitigate carbon emissions. This leads to an anticipated rise in temperature of around 2.7 °C by 2100. Finally, SSP585 is a business-as-usual scenario where little is done to reduce carbon emissions, fossil-fuelled development continues and the temperature rises by around 4.4 °C by 2100. We will explore these various scenarios and how they impact insurance uptake out to 2100.[2]

Fig. 2 illustrates how the standardized climate risk metrics evolve over time on average across postcodes. The cyclone risk increases by more than 0.7 standard deviations from 2000 to 2100 under SSP585.[3] The risk of extreme precipitation rises by around 0.3 standard deviations under SSP585 but falls slightly under SSP126. Wildfire risk rises by almost 0.25 standard deviations from 2000 while there is a relatively modest change in average flood risk.

3.2. Household panel data

The HILDA Survey provides annual data on a representative sample of around 10,000 households across Australia. The first wave of the HILDA Survey was undertaken in 2001 and the latest available data is for 2021. Two features of HILDA are particularly important for our study.

First, the HILDA Survey included a question in the 2014 and 2018 waves as to whether the household had home contents insurance. Note here that perhaps of greater interest is whether a household has home-building insurance. Unfortunately, HILDA did not ask this question. However, it is likely that the climate risk drivers, industry pricing, and the household decision-making process around these two sorts of home hazard insurance are similar. This means that though we focus on home contents insurance, our results are also likely to provide relevant insights as to the dynamics of home building insurance. Moreover, prior research has indicated a very high correlation between having home-contents and home-building insurance. For example, Booth and Tranter (2018) surveyed 1155 households in Australia and found that 79.1% had both home contents and home building insurance. Only 5.6% had just home contents insurance with a further 4.8% having only home building insurance.

Second, the HILDA Survey includes the postcode of residence of the household. This allows us to merge the household panel data with the climate hazard data.

[1] CMIP stands for Coupled Model Intercomparison Project and represents a suite of models that are run by climate modelling experts around the world. Their outputs inform the Intergovernmental Panel on Climate Change assessment reports. There have been various versions of CMIP. CMIP6 is the most recent and includes around 100 models from 49 modelling groups (Hausfather, 2019).

[2] However, note that for cyclones we only have SSP585, so this is used in all cases. For floods we only have SSP245 and SSP585 and the former is used for SSP126.

[3] In the Online Appendix we illustrate the complexity and nuance of the spatial evolution of cyclone risk by comparing maps of the risk in 2000 with that in 2100.

Table 1
Climate risk summary statistics (by Postcode, 2000).

Risk	No. obs.	Mean	SD	Min.	Percentiles			Max.
					25th	50th	75th	
Cyclone	2641	0	1	−0.32	−0.32	−0.32	−0.32	9.20
Wildfire	2641	0	1	−0.27	−0.26	−0.21	−0.07	13.04
Flood	2641	0	1	−0.32	−0.32	−0.30	−0.13	20.38
Extreme Precipitation	2641	0	1	−0.85	−0.79	−0.52	0.63	5.29

Notes: The mean and standard deviation (SD) are 0 and 1 by construction as the climate risk scores are standardized relative to the average postcode score in 2000.

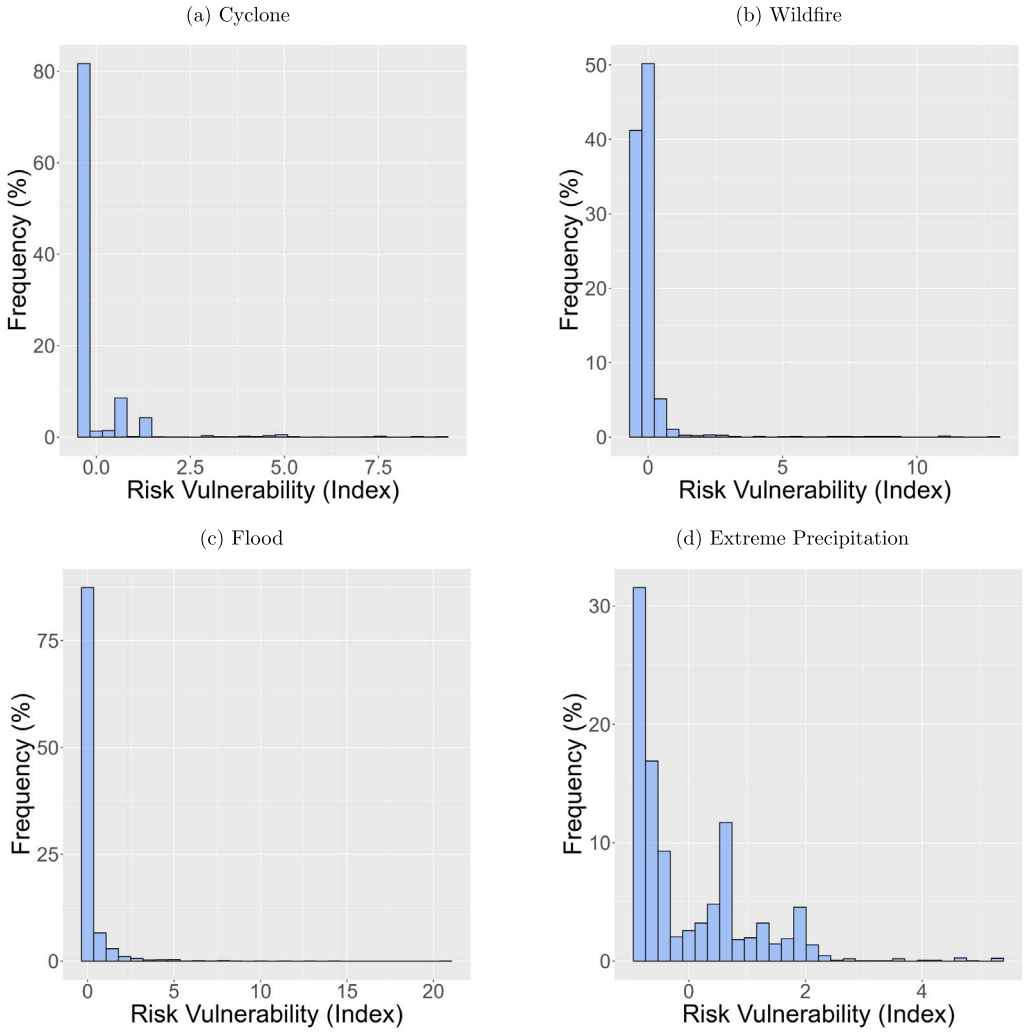

Fig. 1. Distribution of climate physical risks across postcodes (2000).
Notes: The Risk Vulnerability (Index) reflects the number of standard deviations from the mean in the year 2000.

Table 2 describes the variables from the HILDA Survey that we use in our regression model. The dependent variable is 'Insurance'. This is equal to one when a household has home contents insurance and zero otherwise. Around 74% of households have insurance and this ratio is very similar across both 2014 and 2018.

The control variables that we will include in the regression model are also listed in Table 2 these include the age, gender, labour force status, educational level, and a risk aversion indicator for the household head. This risk aversion indicator was proposed by Johar et al. (2022) and is equal to one when respondents answer that they are 'not willing to take financial risks' with their spare cash.[4] We also include whether the household owns their property, the household type, the number of bedrooms in the home, household wealth and disposable income. In the case of the latter two variables we divide by the inflation rate to put the variables in real terms. This makes the values from 2014 and 2018 waves of the HILDA Survey comparable.

4. Methodology

The focus of our methodology is twofold. First, to model, explore, and understand the relationship between climate risks and the decision

[4] The other possible responses are; 'Takes substantial risks expecting substantial returns', 'Takes above-average risks expecting above-average returns', 'Takes average financial risks expecting average returns' or 'Never has any spare cash'.

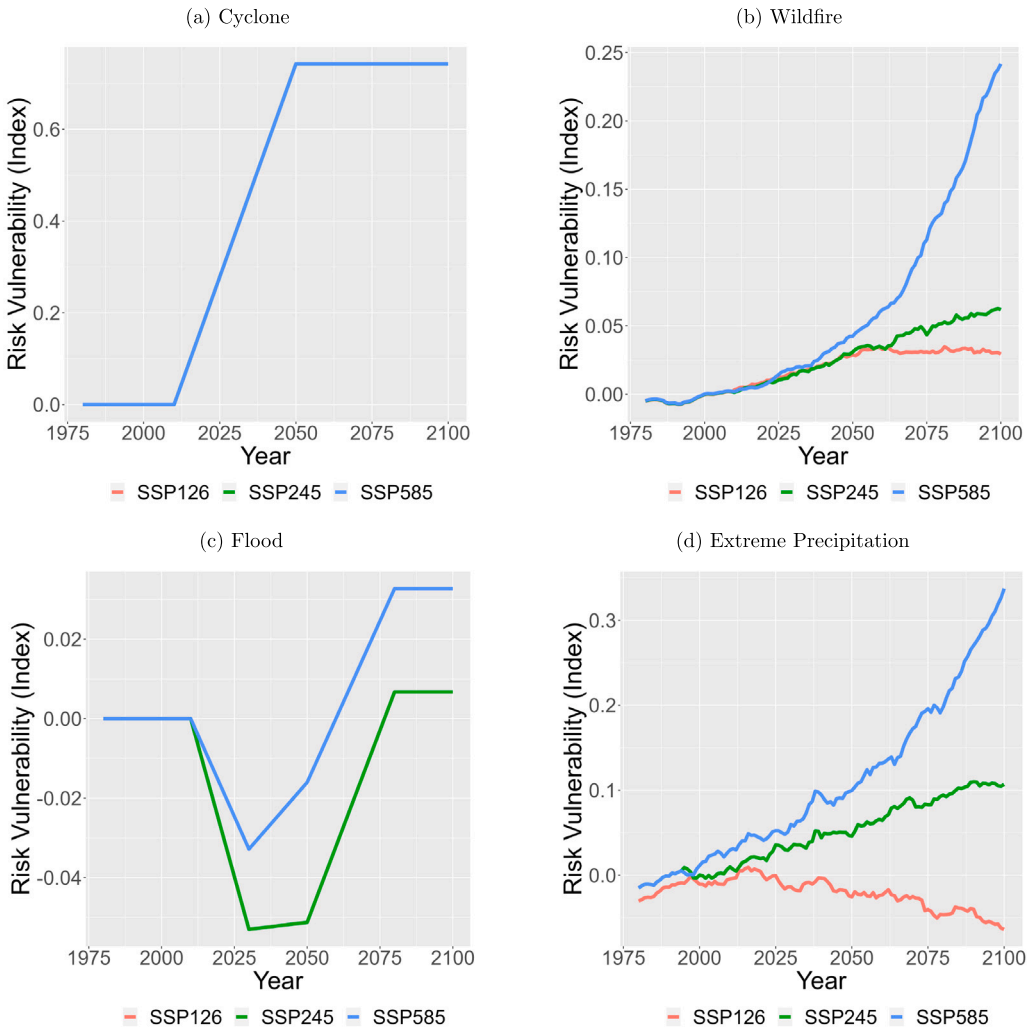

Fig. 2. Trends in climate physical risks. Notes: The Risk Vulnerability (Index) reflects the number of standard deviations from the mean in the year 2000.

to purchase insurance. Second, to develop a model that enables us to project the probability a household purchases insurance into the future as a function of climate scenarios.

To meet these objectives we estimate various linear probability models. An alternative approach would be to estimate a logistic or probit regression model. However, the linear probability model has some advantages. It is easier to interpret the coefficients. But more importantly, it has an exact additive decomposition in its components. This will be important later when we project the effect of the evolution of climate risks on insurance uptake—the linear probability model enables us to provide a decomposition of the various climate drivers.[5] Our initial model has the form,

$$y_{ipt} = \mathbf{x}_{it}^{T}\boldsymbol{\alpha} + \sum_{k=1}^{K} \beta_k r_{ptk} + e_{ipt} \tag{1}$$

Here y_{ipt} is an indicator variable equal to one when household i has home-contents insurance and zero otherwise. The index p denotes the postcode in which the household lives and t is the year. The model has two types of explanatory variables.

First, $\mathbf{x}_{it}$ denotes a vector of characteristics relating to the household, the household head and the home, that may explain insurance uptake. The parameters to estimate are denoted $\boldsymbol{\alpha}$. This data comes from the HILDA Survey and was discussed in the previous section. The variables included in the model are plausible insurance demand shifters.

Second, r_{ptk} denotes climate physical risk indicator k for year t. The corresponding coefficients are $\beta_1, \beta_2, \ldots, \beta_K$. The climate risk variables relate to the price and cost of insurance. But also reflect the benefits to households from insuring against various risks. In this sense, the climate risk indicators will influence both demand and supply of home insurance.

The model in Eq. (1) specifies a reduced form relationship between the quantity of insurance purchase and exogenous factors. Of particular note is that our quantity equation does not include the price of insurance. This data is commercially sensitive and not publicly available in Australia.[6] Our model reflects the outcome of the interaction of demand and supply for home insurance in local areas. The key feature of the model is that it tracks how the equilibrium evolves across locations as a function of exposure to climate physical risks. This enables us

[5] However, we have also replicated our results using the logistic regression model. These are included in the Online Appendix. The results for the logistic regression model are qualitatively and quantitatively similar to those from the linear probability model.

[6] Note that the price and quantity of insurance are likely to be endogenous. Hence if price data were available then an instrumental variable would be needed to undertake structural estimation of the demand and/or supply equations.

Table 2
Household panel summary statistics (2014 and 2018).

Variable	No. obs.	Mean	SD	Percentiles		
				25th	50th	75th
Insurance	18,403	0.74	0.44	0.00	1.00	1.00
2014	9167	0.74	0.44	0.00	1.00	1.00
2018	9236	0.73	0.44	0.00	1.00	1.00
Age	18,403	49.27	18.25	33.00	48.00	63.00
Female	18,403	0.51	0.50	0.00	1.00	1.00
Owner	18,403	0.62	0.49	0.00	1.00	1.00
No. of Bedrooms	18,403	3.10	1.09	2.00	3.00	4.00
Disposable Income ($000)	18,403	85.20	67.60	40.28	71.65	113.06
Wealth ($m)	18,403	0.96	1.42	0.11	0.58	1.21
Risk Averse	18,403	0.37	0.48	0.00	0.00	1.00
Household Type						
Couple with Dependents	4741	–	–	–	–	–
Coupled without Dependents	5931	–	–	–	–	–
Lone Parent	1088	–	–	–	–	–
Lone Person	5450	–	–	–	–	–
Other	1193	–	–	–	–	–
Education						
Certificate III or IV/Diploma	11,349	–	–	–	–	–
Less than Secondary School	4536	–	–	–	–	–
Secondary School	2518	–	–	–	–	–
Labour Force Status						
Employed	11,556	–	–	–	–	–
Not in Labour Force	6307	–	–	–	–	–
Unemployed	540	–	–	–	–	–

Notes: Statistics are for both the 2014 and 2018 waves of the HILDA Survey unless indicated otherwise. SD denotes standard deviation. Age, Female, Risk Averse, Education and Labour Force Status relate to the household head while other variables relate to the household.

to understand how insurance purchase may evolve as the climate changes. Because we estimate a reduced form, higher climate risks could either increase or decrease insurance uptake. On the supply-side higher climate risks will increase the cost of providing actuarially fair insurance. On the demand-side higher climate risk will raise prices and reduce insurance purchase but also increase the benefits of insurance to policyholders. Our model documents how these effects balance out across Australia.

These dynamics mean that the relationship between climate risks and insurance uptake are likely to be complex. To better explore how these effects impact each other we also estimate a number of more flexible linear probability models which allow for spline effects in the climate physical risk variables. This regression model has the form,

$$y_{ipt} = \mathbf{x}_{it}^{T}\boldsymbol{\alpha} + \sum_{k=1}^{K} s\left(r_{ptk}\right) + e_{ipt} \tag{2}$$

Here $s(r_{ptk})$ denotes a spline function of the risk k. Spline functions place little a priori structure on the relationship. In our implementation we have used cubic splines. This creates knots along the span of the variable and estimates a smooth function between each segment. Compared with a linear variable, which has a single degree of freedom, spline functions can have effective degrees of freedom greater than one. We report the effective degrees of freedom in our results. Higher degrees of freedom will always improve the in-sample fit of the model so we choose the effective degrees of freedom optimally by selecting the value which leads to the most accurate out-of-sample prediction.[7] This model has the advantage over Eq. (1) that the impact of the climate risks can be more complex and both non-linear and non-monotonic. As we will see in our discussion of the results this is an important extension.

Our second objective is to project how insurance uptake may evolve in response to climate change. To address this question we fix all non-climate variables. Then we apply our insurance uptake model and the projected climate risk series out to 2100 to the population of households observed in 2014 and 2018. In essence, we are using observed variation in cross-sectional insurance purchase and climate risks to understand how the rate of insurance uptake would evolve for the present sample were they to face the climate risks that are projected for the rest of this century. In this sense, it is not a forecast. A true forecast is challenging because a wide range of factors will influence insurance uptake including technological changes in assessing a home's vulnerability to physical risks as well as changes in household income and wealth, family composition, size and location of dwellings (Zander et al., 2020), homeownership rates, and many other things. Our approach abstracts from this and focuses on the impacts of climate risks for current households. This answers the key question of interest—how will changes in climate physical risks influence insurance purchase within the current context?

5. Results

This section discusses our results. We begin by discussing our model of the drivers of insurance uptake. We then turn to what this model says about the rate of insurance purchase out to 2100 as a result of climate risk.

5.1. Regression models of insurance uptake

Our first objective is to understand the factors which influence insurance uptake in Australia with a particular focus on the role of climate risks. To do this we estimate several regression models of insurance purchase, which include a range of explanatory variables. The results are shown in Table 3.

Model 1 includes the climate risk variables and a range of explanatory variables derived from the HILDA Survey. This includes data from 2014 and 2018 with the climate hazard data matched for the corresponding year. This model has a reasonable R^2 of 0.388. First let us examine the coefficients on the control variables. Our results show that owners are 27.4 percentage points more likely to have insurance while if the household head is older or female the likelihood of insurance purchase increases. Households with higher levels of wealth, higher incomes, and larger homes (reflected in the number of bedrooms) are

[7] To estimate the spline regression models the approach of Wood (2017) is used. This is reflected in the R package `mgcv`. Here an approximation to cross-validation is implemented to select the splines' effective degrees of freedom.

Table 3
Regression results.

	Model 1	Model 2	Model 3	Model 4
Intercept	−0.566***	−0.584***	−0.487***	−0.701***
	(0.053)	(0.053)	(0.076)	(0.074)
HILDA Survey 2018	−0.025***	−0.024***	—	—
	(0.005)	(0.005)	—	—
Cyclone	0.012***	—	—	—
	(0.003)	—	—	—
Extreme Precipitation	−0.033***	—	—	—
	(0.003)	—	—	—
Flood	−0.008***	—	—	—
	(0.002)	—	—	—
Wildfire	−0.001	—	—	—
	(0.005)	—	—	—
Age	0.003***	0.003***	0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.036***	0.037***	0.044***	0.030***
	(0.005)	(0.005)	(0.008)	(0.007)
Log Real Household Disposable Income	0.024***	0.024***	0.017**	0.032***
	(0.005)	(0.005)	(0.007)	(0.007)
Owner	0.274***	0.273***	0.257***	0.290***
	(0.008)	(0.008)	(0.011)	(0.011)
No. Bedrooms	0.022***	0.021***	0.021***	0.021***
	(0.003)	(0.003)	(0.004)	(0.004)
Log Real Household Wealth	0.052***	0.052***	0.053***	0.051***
	(0.002)	(0.002)	(0.003)	(0.003)
Risk Averse	0.024***	0.024***	0.024***	0.025***
	(0.005)	(0.005)	(0.008)	(0.008)
Household Type:				
Couple without Dependents	−0.018**	−0.019***	−0.015	−0.023**
	(0.007)	(0.007)	(0.010)	(0.010)
Lone Parent	−0.010	−0.012	−0.016	−0.007
	(0.012)	(0.012)	(0.017)	(0.017)
Lone Person	−0.035***	−0.035***	−0.038***	−0.033***
	(0.009)	(0.009)	(0.012)	(0.012)
Other	−0.070***	−0.070***	−0.081***	−0.062***
	(0.012)	(0.011)	(0.016)	(0.016)
Education:				
Less than Secondary School	−0.003	−0.004	−0.002	−0.004
	(0.007)	(0.007)	(0.009)	(0.009)
Secondary School	−0.003	−0.003	0.003	−0.010
	(0.008)	(0.008)	(0.011)	(0.011)
Labour Force Status:				
Not in Labour Force	−0.038***	−0.036***	−0.044***	−0.029***
	(0.007)	(0.007)	(0.010)	(0.010)
Unemployed	−0.071***	−0.070***	−0.076***	−0.065***
	(0.016)	(0.016)	(0.022)	(0.022)
Spline Degrees of Freedom:				
Cyclones	—	3.050***	1.423	3.567***
Extreme Precipitation	—	2.466***	2.398***	2.200***
Flood	—	1.001***	1.002**	1.011*
Wildfire	—	2.444	1.001	1.003
R^2	0.388	0.390	0.369	0.410
No. obs.	18 403	18 403	9167	9236

Notes: Standard errors are shown in parentheses. Spline Degrees of Freedom estimates the effective number of terms which are included in the model. A value of 1 denotes that the spline is linear with larger values indicating the spline has greater flexibility. Models 1 and 2 use data from both 2014 and 2018. Model 3 only uses data from 2014 and Model 4 only uses data from 2018.

*** Significance levels: $p < 0.01$.

** Significance levels: $p < 0.05$.

* Significance levels: $p < 0.10$.

more likely to have insurance. We also find that household type and employment status play a role in the decision to purchase insurance. Household heads who are recorded as being risk averse are around 2.4 percentage points more likely to purchase insurance. There is also a slightly lower rate of insurance take-up in 2018 relative to the 2014 wave. Now turning to the climate risk variables. We find a negative and statistically significant relationship between extreme precipitation and flood and the likelihood of insurance purchase. For extreme precipitation, a one standard deviation increase in risk reduces insurance uptake by around 3.3 percentage points while for flood it reduces insurance uptake by 0.8 percentage points. The coefficient for cyclone is positive—a one standard deviation increase in cyclone risk raises insurance by around 1.2 percentage points. These effects are economically meaningful drivers of insurance uptake. The coefficient for wildfire is insignificant. Our results provide some contrast with the literature. Atreya et al. (2015) and Bradt et al. (2021) generally found higher insurance coverage for regions more exposed to climate risks. We find this for cyclones but not for flood or extreme precipitation.

In Model 2 we include all the variables in Model 1. However, the climate risk variables are included using a spline function. This results in a slightly improved R^2 of 0.390. The spline functions are shown in Fig. 3. The x-axis of these figures shows the exposure of the household to the climate risk measured in the number of standard deviations from the mean. The y-axis is the percentage point effect on the likelihood of insurance purchase measured as a decimal. The spline for wildfire is essentially zero while for flood it is linear and

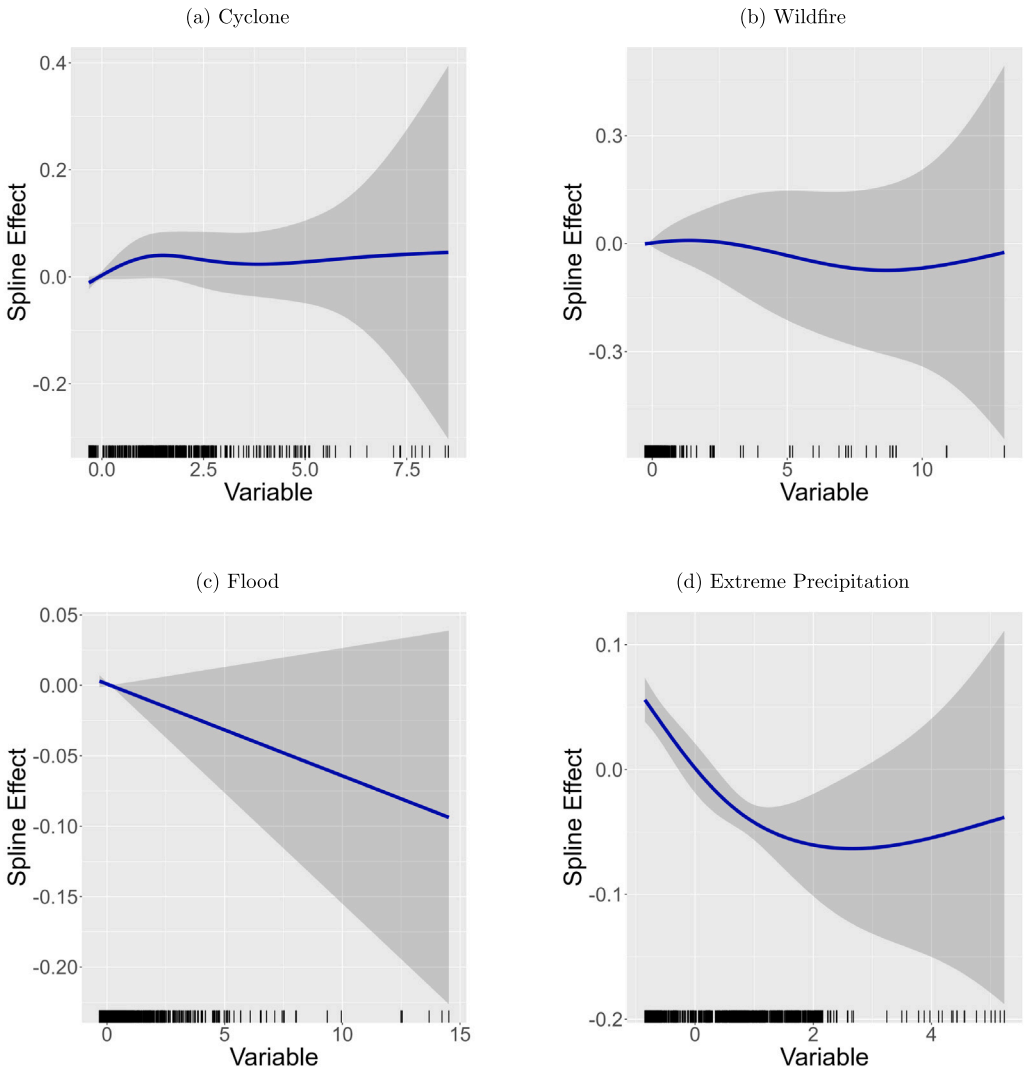

Fig. 3. Insurance purchase: Spline effects for climate physical risk variables.
Notes: The shaded area provides a 95% confidence interval. The short vertical lines at the bottom of the chart denote the observations.

downward-sloping, as we found in earlier models. The effect of cyclone risk and extreme precipitation on insurance purchase is more complex. For cyclone risk, there is a non-monotonic relationship between risk and insurance purchase. There is an initial rise in the likelihood of insurance purchase as cyclone risk rises. This indicates that the increased demand outweighs the supply-side effects of rising cost due to increased cyclone risk. However, after around one standard deviation from the mean, the curve becomes relatively flat. The impact of extreme precipitation on insurance purchase is steeply downward sloping until around 2 standard deviations from the mean and then slopes gently upward.

We estimate two further models to explore the robustness of our results. Model 3 is estimated over data from 2014 while Model 4 uses data from 2018. Both models include the same variables as in Model 2. The results in Table 3 illustrate the robustness of the parameter estimates across these two samples. The spline functions of the climate risk variables are also similar.[8]

[8] Plots of the spline functions for each variable in the 2014 and 2018 models are included in the Online Appendix.

Our results are broadly consistent across specifications and over the two waves of the HILDA Survey. In terms of the literature, our results emphasize the links between advantage – reflected in income, wealth, homeownership, and home size – and the likelihood of insurance purchase. This contrasts somewhat with Booth and Kendal (2020) who downplayed these links. Similar to Atreya et al. (2015) we found that older people, and those with higher incomes, are more likely to purchase insurance. In contrast, they found that areas with high homeownership rates were less likely to purchase insurance. Though their results were based on comparing county-level averages not household-level data as in our case.

Finally, we illustrate the relationship between climate risk exposure and insurance purchase by comparing a household's combined climate risk score, based on our regression estimates, with their likelihood of having insurance. This is done in Fig. 4. Here we use Model 2, which used all the data from 2014 and 2018. The combined climate risk score on the x-axis is the sum of the spline components for each household (i.e., from Eq. (2) it is $\sum_{k=1}^{K} s\left(r_{ptk}\right)$). The y-axis measures the likelihood of insurance being purchased by the household. In the observed data this is either zero or one so we estimate a spline of this value as a function of the combined climate physical risk score.

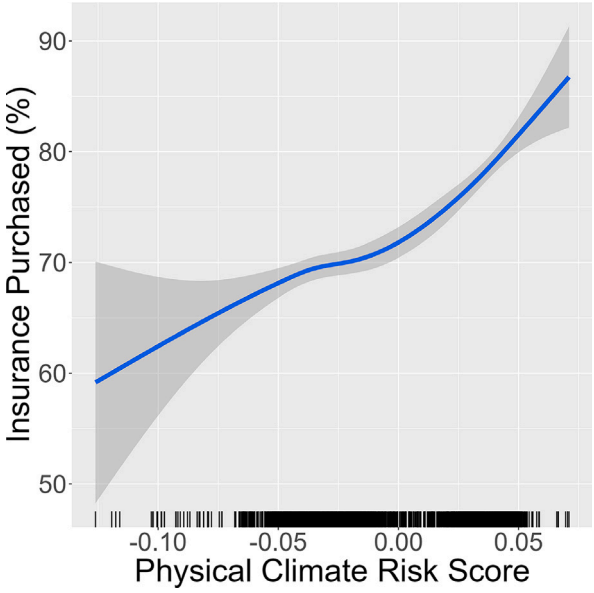

Fig. 4. Insurance purchased vs regression physical risk score.
Notes: The shaded area provides a 95% confidence interval. The short vertical lines at the bottom of the chart denote the observations.

The figure indicates a strongly upward-sloping relationship—households that have lower exposure to climate physical risks (and hence a higher score) have a higher likelihood of having insurance. If we compare the household with the highest exposure to climate risks to those households with the least – roughly the difference between around −0.15 and around 0.10 – then we see a difference in the likelihood of having insurance of around 25 percentage points. This reinforces our earlier regression results that climate risks are major drivers of insurance purchase. However, a further key insight from this figure is how insurance markets operate in the presence of significant climate risks. At the left-hand end of the figure, we see that households with the greatest climate risk exposure still have a propensity to purchase insurance of around 60%. These results illustrate that many households can still access insurance even when risks are elevated. This provides a more sanguine view about the impacts of climate change on insurance markets than Tesselaar et al. (2020) who projected that flood insurance availability may disappear for certain European communities.

5.2. Scenario projections of insurance uptake

The second question that we address is the impact that changes in the climate are likely to have on insurance uptake. To undertake these projections we use Model 2. This included splines for the climate risk variables and a range of household characteristics. We consider three different scenarios SSP126, SSP245, and SSP585 and proceed as outlined above. Our results for Australia are illustrated in Fig. 5. Here we have averaged over the households in the HILDA dataset—relying on the fact that the HILDA Survey is a nationally representative sample.

The results show a decline of just over 1 percentage point in insurance uptake under SSP585—the scenario where the climate changes most significantly. Here the rate of insurance purchased falls from around 73.5% in 2000 to around 72.5% in 2100. In the context of the dispersion in insurance uptake across postcodes and states in Australia, this is a relatively modest decline. The fall in insurance uptake is much smaller for the SSP245 scenario and amounts to around 0.25 percentage points. In the more optimistic SSP126 scenario, where there is a more limited change in the climate, there is an increase in insurance uptake over the period of around 0.5 percentage points.

Fig. 6 shows the additive contributions of each of the climate risk components to the overall change in insurance uptake. This shows that the main driver of the decline in insurance uptake in SSP585 and SSP245 is the effect of extreme precipitation. The contribution is the spline effect for each variable—in a linear regression context this can be thought of as the 'variable multiplied by the coefficient'. Extreme precipitation has a relatively large effect because the impact on insurance uptake is large (see Fig. 3) and the change in the variable over time is also large (see Fig. 2). The impact of the other climate risk factors is quite small. This is because the spline effects for cyclone, flood, and wildfire are relatively small (see Fig. 3). Also, in the case of flood, the average change in vulnerability to this hazard is relatively modest (see Fig. 2).

As we have noted, there is a significant spatial dimension to climate change. Some states are more highly exposed to certain climate risks and these risks evolve at different rates over time. Fig. 7 plots the projections of insurance uptake by state for each SSP scenario. We find significant differences across Australia's eight states and territories.

In New South Wales (NSW), Victoria (VIC), South Australia (SA) and the Australian Capital Territory (ACT), the primary driver of the decline in insurance uptake under SSP585 is the increase in extreme precipitation. This decline is particularly marked for the ACT which sees insurance uptake fall by around 3 percentage points in SSP585 and NSW with a 2 percentage point decline. Tasmania (TAS) is an interesting hybrid case where a reduction in flood risk increases insurance purchase and counterbalances the downward push from extreme precipitation. Queensland (QLD), Western Australia (WA), and the Northern Territory (NT) are the regions that are particularly affected by cyclones. Queensland's exposure to cyclone risk is relatively high in 2000 and increases throughout the century.[9] This compares with WA and the NT where the risk is somewhat lower and only moderately increases. These effects, coupled with the non-linear effect of cyclones on insurance purchase shown in Fig. 3, lead to differential effects

[9] This is illustrated in Figures A.1 and A.2 available in the Online Appendix.

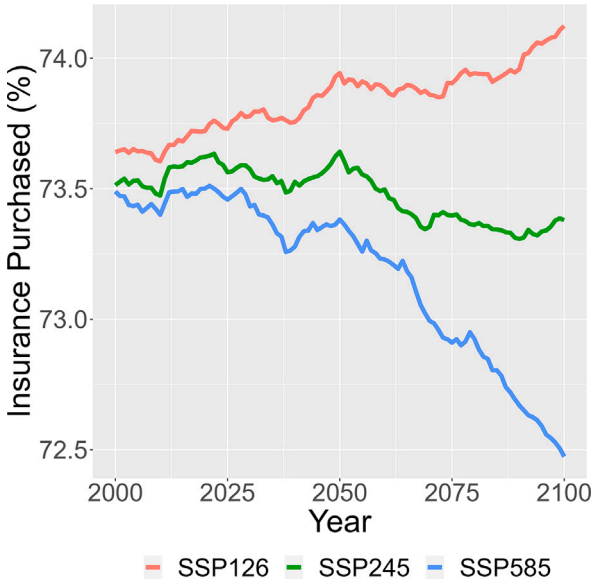

Fig. 5. Projections of home-contents insurance purchase likelihood (%).

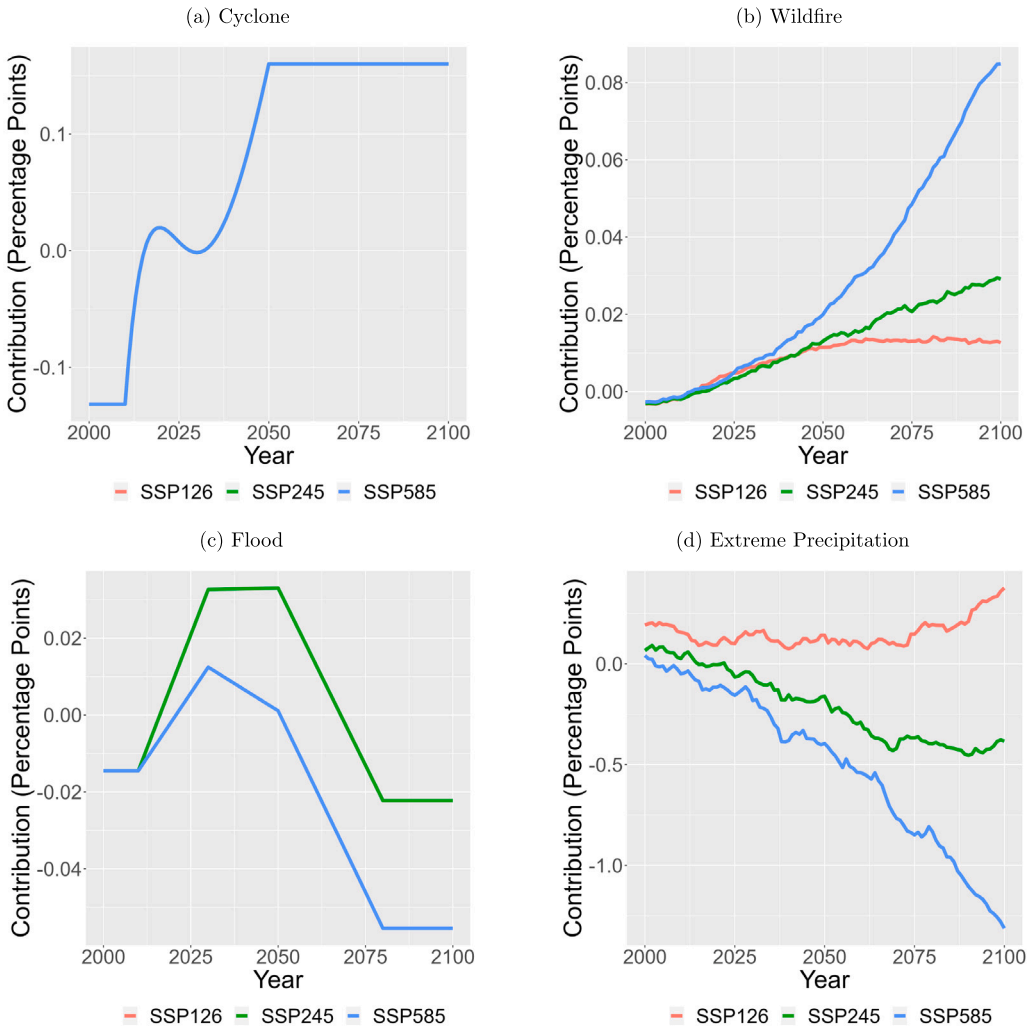

Fig. 6. Contribution of climate physical risks to insurance purchase projections.

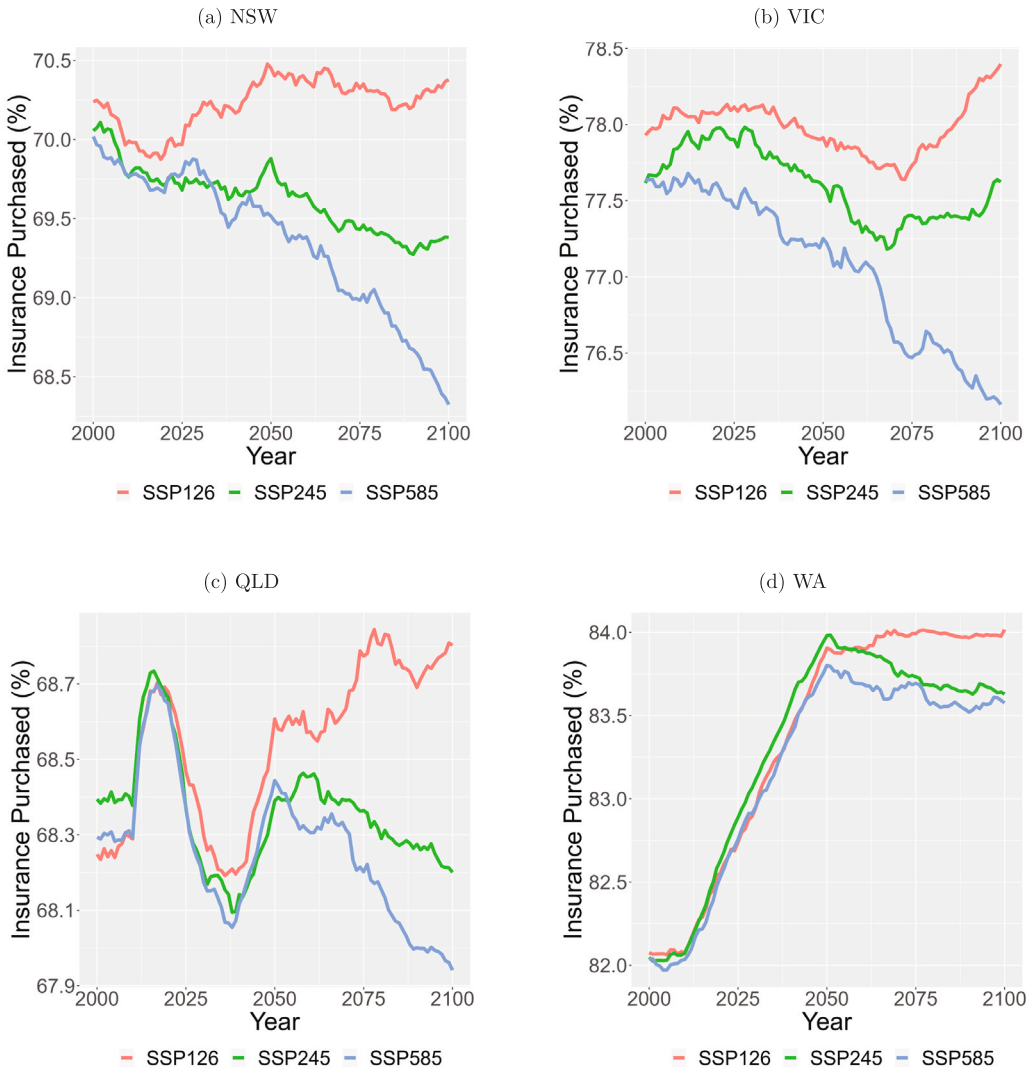

Fig. 7. Projections of home-contents insurance purchase likelihood (SSP by State, %).

on these states and territories. Queensland sees a modest decline in insurance purchase. However, WA and NT see an increase in insurance purchase as their main population centres are on the lower-risk part of the cyclone spline function.

To round out our scenario results we provide some insight into the inherent uncertainties in these projections. The climate risk data reflects a range of uncertainties both from the underlying physical models as well as the models used to downscale the results to local areas, such as postcodes. Our prior results reflect the median projected outcome for each climate risk in each postcode over time. To understand the uncertainty around our projected rate of insurance uptake we have rerun our projections using both a lower bound outcome (16th percentile) for each climate risk and an upper bound outcome (84th percentile). The results are shown in Fig. 8 along with the simulation results for the median climate risk outcomes shown previously for SSP585. What is clear is the very wide range that is obtained by comparing the upper and lower bounds. In 2100 the likelihood of insurance purchase ranges from just under 76% to around 70%—a range of 6 percentage points. This compares to the 1 percentage point drop we found in insurance uptake over this period for the median climate risk outcomes. However, the trend insights provided by the median are reinforced with both the upper and lower bounds declining over this period.

6. Conclusion

This study has examined the relationship between climate physical risks and insurance uptake in Australia. We combined data at the household level—on whether home contents insurance was purchased and household characteristics—with estimates at the local geographic level of the likelihood of climatic hazards—flood, wildfire, cyclone and extreme precipitation. This data enabled us to build a model of the drivers of insurance demand. Our particular focus was on how climate risks influence insurance demand after controlling for household characteristics. We then used this model, and projections of possible climate outcomes, to explore how insurance uptake is likely to evolve as a function of climate change out to 2100.

Our results emphasize that the relationship between insurance uptake and climate risks is strong but complex. For cyclones, we find that for lower levels of risk, an increase in risk leads to a rise in insurance uptake. While for flood and extreme precipitation, we find high risk leads to lower insurance uptake—though for extreme precipitation the effect was non-linear and non-monotonic. The risk of wildfire had a limited impact on insurance uptake. Perhaps the most surprising aspect of our results is our projection of a relatively modest impact

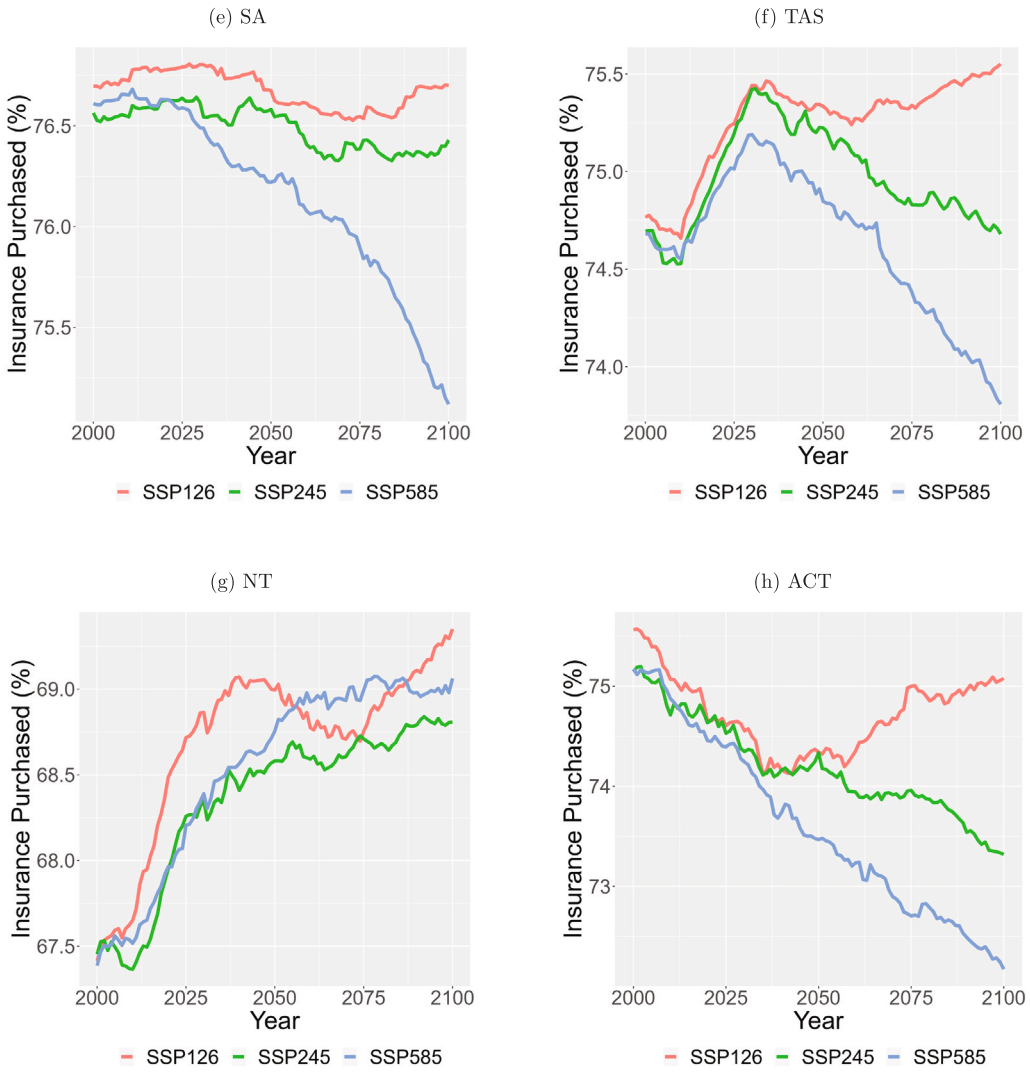

Fig. 7. (*continued*).

on insurance uptake in Australia from climate change. We explored three prospective climate scenarios—these implied temperature rises of around 1.8 °C, 2.7 °C or 4.4 °C by 2100. At a national level, we project a decline of around one percentage point in insurance uptake under the scenario with the largest temperature rise. However, there is significant variation at the state and territory levels in Australia. Some regions see a decline of up to three percentage points in insurance uptake while others see rises.

The results are particularly interesting in light of the active debate around climate change and insurance availability. The gradual and relatively modest decline we find in insurance uptake provides some important insights but also has some caveats. First, there is significant uncertainty in these projections given the challenges of downscaling projections from geographically aggregated climate models. Second, our climate risk projections focus primarily on the increased incidence of events and do not fully reflect the likely increase in severity. Third, our focus is at the postcode level, rather than on individual properties. Improvements in modelling methods likely mean that insurance providers can more precisely identify high-risk homes where premiums may need to rise to be actuarially fair. This is leading to greater geographic dispersion in premiums at fine geographic scales. However, a fundamental insight that comes out of the analysis is that climate risks and their impacts evolve over long time spans. This is reflected in our projections which anticipate a relatively modest and gradual reduction in insurance uptake across Australia over the coming century.

CRediT authorship contribution statement

Daniel Melser: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing, Project administration. **Trinh Le:** Conceptualization, Data curation, Project administration. **Ummul Ruthbah:** Conceptualization, Data curation, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108195.

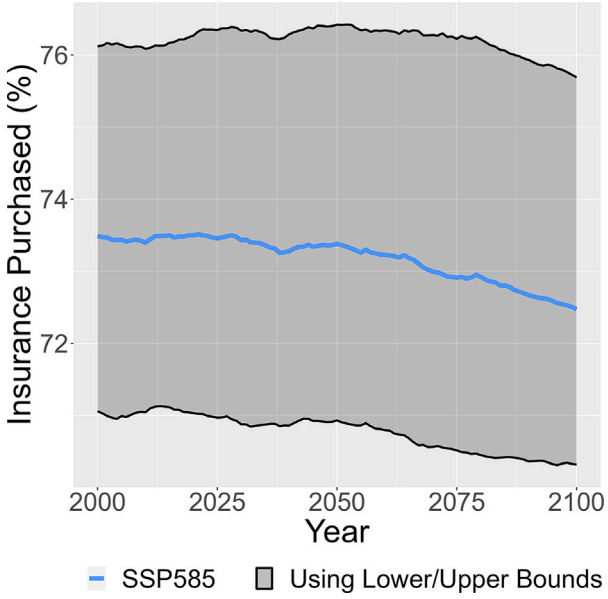

Fig. 8. Projections of insurance purchase likelihood with lower and upper bounds.

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