Sheltering from Climate Risks

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Abstract

Using administrative data on flood insurance, I document pervasive heterogeneity in the adaptive investments of American households. In response to increasing climate risks, affluent home-owners tend to elevate their properties whereas poorer households rely on higher levels of insurance. I develop a climate risk model with heterogeneous agents, housing insurance and investments in adaptation that can account for these findings. Counterfactual simulations reveal that as climate risk rises, financially constrained households avoid investing in adaption in favour of insurance subsidised by the government. As a result, the poorest households hold an increasing share of the housing stock most exposed to climate risks.

Keywords: climate change, adaptation, insurance, inequality

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1 Introduction

As extreme weather risks intensify with the climate crisis, we face the question of how to manage and mitigate increasing climate damages. The IPCC emphasises that even with small levels of warming, heatwaves, extreme rainfall, storms and droughts will become more frequent, and the most extreme disasters are particularly likely to become more common.[1] Examples abound of these risks. For instance, in the summer of 2021, Germany and surrounding countries suffered $54bn of losses following flash floods, amounting to the costliest natural disaster on record for Germany (Munich Re, 2022).

Damage to housing is one of the most prominent avenues of exposure to climate risk which households may need to mitigate. Directly insuring risk is one classic option; governments frequently subsidise or heavily regulate insurance to ensure it is affordable and available to households, and despite this, insurance coverage during natural disasters is often low. Another approach is to invest in adaptation, to reduce the damage caused when climate risks occur. Little is known about how households may differentially adopt these approaches and the consequences of these decisions for aggregate climate damages.

To address this question, I first present empirical evidence of household responses to rising flood risk in the United States. Flooding is one of the most substantial climate risks in the US.[2] Using records of over 70 million flood insurance policies from administrative microdata from the National Flood Insurance Program, I study household decisions to take out flood insurance, compared to a particular adaptive method, home elevation. Home elevation mitigates risks by raising the lowest floor of a house above typical flood elevations, and is a prominent method for mitigating property flooding in the USA (Wing et al., 2022).[3] I use details of the insurance policies to construct novel panels of elevation and insurance at the property level. This provides granular detail on individual households' changing decisions to mitigate risk.

As climate change occurs very gradually, I face the common problem of how to measure the impacts of increasing climate risk. To combat this, I adopt the novel approach used in recent literature, measuring the responses to changes in information transmitted via social networks.[4] I proxy changing climate risk by creating a measure of flood risk awareness based

[1] Intergovernmental Panel on Climate Change (IPCC) (2023)

[2] Of the top 10 most damaging US climate disasters between 1980-2019, 8 were due to widespread flooding (Bates et al., 2021; NOAA, 2020).

[3] Kousky and Michel-Kerjan (2017) find that elevation reduced flood insurance claims by 16%.

[4] Bailey, Cao, Kuchler, Stroebel, and Wong (2018) show the broad applicability of social networks as an information transmission mechanism, and this approach has been used in the cases of housing markets (Bailey, Cao, Kuchler, and Stroebel, 2018; Bailey, Dávila, Kuchler, and Stroebel, 2019; Bailey, Dávila, Kuchler, and Stroebel, 2019), and insurance markets (Xu and Box-Couillard, 2024; Hu, 2022; Ratnadiwakara, 2021).

on the flood experiences of households' social network, using the Facebook friendship network data from Bailey, Cao, Kuchler, Stroebel, and Wong (2018). Assuming that households respond to information on *actual* rises in risk in a similar way to this transmission of information about risk, this suggests how households may respond to future rises in climate risk.

I find that households increasingly take out flood insurance in response to rising awareness of flood risk. This suggests the transmission of risk awareness via the social network does indeed occur.[5] Home elevation also becomes more common. The key and novel element of my results is that I am able to compare the relative responses of take-up versus adaptation via elevation; overall, the take-up of insurance is about fourteen times more likely than elevation, by four years after the shock. Responses are also highly persistent, suggesting that once alerted to climate risk, households remain persistently more aware and act to mitigate their risk.

Moreover, there is considerable heterogeneity in responses. Low income households are overall less responsive to shocks, and much more reliant on insurance relative to elevation. Relative to elevation, they are about twenty-five times more likely to have taken up insurance. Low income households invest relatively little in adapting to reduce the damage caused by climate change. In contrast, high income households are relatively more likely to rely on adaptive investments to mitigate climate risks. Households in high income areas are about four times more likely to invest in adaptation than low income households. I show how migration interacts with these results, finding that areas with relatively low levels of relocation drive adaptation. I also show how these results are robust to a range of alternative approaches to constructing my flood awareness proxy.

Motivated by these empirical findings, I develop a model of climate risk to understand the broader implications of household responses.[6] Households are heterogeneous, subject to borrowing constraints and uninsurable idiosyncratic income risk. Households hold housing as both a financial asset and good which delivers utility. Housing is subject to disaster risk if a flood hits. Households can choose to mitigate the financial impact of this risk by purchasing insurance, or reduce the damage from the risk by adapting their homes. Both housing and home elevation are illiquid assets, subject to adjustment costs, unlike savings in liquid bonds. I calibrate the model to represent high flood risk areas in the US. I solve for a transition as flood risk gradually rises, solving for equilibrium in the local housing market.

[5] These results echo those of Xu and Box-Couillard (2024), Hu (2022), and Ratnadiwakara (2021).

[6] The set-up of the model follows in the footsteps of Fried (2022), who outlines a seminal macroeconomic model of climate risk, which she uses to estimate the existing total adaptive capital in the US as 1% of the total US capital stock.

The model reflects the responses of insurance and adaptation observed in the data. In response to a rise in flood risk, insurance and elevation increase, with insurance rising relatively more. The relative response of insurance is about six times that of elevation. Compared to the relative response in the data of fourteen, this is smaller but a similar order of magnitude. This reflects that elevation is relatively more attractive and taken up in the model than the data. High income households drive a rise in home elevation; they are only twice as likely to increase insurance relative to elevation, even more inclined to elevate their homes than in the data (where the ratio is 13). Low income households rely on insurance to insulate themselves from rising flood risk, and fail to adapt their housing.

A decline in demand for more risky housing results in a decline in house prices. In response to this, there is a further, indirect effect which increases low income households' exposure to climate risk. Following the decline in house prices, high income households sell housing, and the housing stock is taken up by low income households. As a result, low income households are more exposed to climate risk and as they fail to invest in adaptation, pay increasing insurance premia. Because of these increasing costs of flood risk, the consumption of low income households falls disproportionately. Overall consumption falls only marginally, and higher income households mitigate their exposure to climate risk by adapting their housing stock, and so their consumption falls only mildly. As a result, climate damage is regressive, falling more heavily on lower income households who hold an increased share of housing and do not invest in adaptation.

The key mechanism driving these heterogeneous responses is the financial constraints faced by households. Households closer to their borrowing constraints - which tend to be lower income - are less inclined to lock up savings by investing in elevated housing. This is because the premium spent on elevated housing is costly to draw down on when negative income shocks occur. Instead, short-term insurance policies are more attractive. This is particularly the case when, as in the data, insurance is subsidised by the government. This heterogeneity is further exacerbated by the gradual nature of increasing climate risks. Households who are financially constrained tend to have shortened financial planning horizons. As a result, they may be less able or willing to make upfront investments in adaptation that would pay out over decadal horizons as risks rise. Instead, households may either choose alternative adaptive mechanisms that cost less in the short term - but may be less effective - or leave themselves more exposed to risk.

My results suggest that subsidies for insurance may paradoxically worsen the damage from climate change. Governments may want to ensure that households do partially mitigate risks, rather than having to self-insure when disasters strike. However, if these subsidies result in reduced incentives to adapt, they can decrease aggregate adaptation and increase the damage caused by climate change. This suggests that reductions in insurance subsidies, such as those made by the Risk-Rating 2.0 pricing methodology, launched by the National Flood Insurance Program in 2021, may be wise. However, using the savings to subsidise adaptation or subsidise loan programmes may help increase the inefficiently low levels of adaptive investment, particularly if targeted at financially constrained households.

Related literature This paper contributes to a growing recent literature on the implications of climate risk, and approaches to adapting to this risk. Fried (2022) is a seminal contribution to this literature, where she develops a macroeconomic model of climate risk and uses the model to infer the amount of adaptation capital and the degree to which adaptation capital reduces the damage from climate change. Bilal and Rossi-Hansberg (2023) develop a spatial model of climate risk, calibrated to match the empirical responses to storms and heatwaves. They use this to understand how climate change may damage the economy and the degree to which investment and migration responses may mitigate damage. Relative to these models, my contribution is two-fold; I focus on the heterogeneity across households and how this can meaningfully change the resulting aggregate impacts of climate change, and I particularly focus on the differences across types of adaptation approaches; insurance and adaptive investments. Van der Straten (2023) also develops a heterogeneous agent model of adaptation to climate risk; her focus is on the importance of mortgages in creating reduced incentives to adapt for credit-constrained households, a complementary channel to the one I model. Balboni (2019) explores how susceptible infrastructure investments in Vietnam are to climate change and sea level rise, modelling the cost of climate damage.

These models build on a long literature on the macro-economic implications of climate change pioneered by Nordhaus (1977), Nordhaus (1992), Nordhaus and Boyer (2000) and developed by Weitzman (2009), Golosov, Hassler, Krusell, and Tsyvinski (2014) and Cai and Lontzek (2019). In this literature, climate damage is modelled as a reduced form damage function, encompassing extreme weather events in addition to a broader range of potential economic impacts of climate change. While often modelled using global models with representative agents, a range of contributions have developed our understanding of the heterogeneity of effects of climate change across space, including Desmet and Rossi-Hansberg (2015), Desmet, Nagy, and Rossi-Hansberg (2018), Desmet, Kopp, et al. (2021), Smith and Krusell (2017), while Desmet, Kopp, et al. (2021) specifically focusses on effects of coastal flooding from sea level rise.

Complementary to these modelling contributions, a wide empirical literature has estimated the economic impacts of climate change. Key contributions include Dell, Jones, and Olken (2012), Deschênes and Greenstone (2007) and Hsiang and Jina (2014), who estimated the economic impacts of temperature variations and extreme weather events. More recently, Nath, Ramey, and Klenow (2024) and particularly Bilal and Känzig (2024) have shown that properly accounting for persistence of climate damages, and using macro-economic data rather than within-country variation, suggests that the economic damages of climate change may be much larger than previously appreciated. A detailed literature has focussed on responses to natural disasters and natural disaster risk, including Deryugina (2017), Deryugina, Kawano, and Levitt (2018), Bakkensen and Barrage (2022), McCoy and Walsh (2018) and Issler, Stanton, Vergara-Alert, and Wallace (2020). I add to this by focussing on how household investments in adaptation respond to awareness of climate risk, rather than realisations of climate risk. Bernstein, Gustafson, and Lewis (2019), Murfin and Spiegel (2020) and Baldauf, Garlappi, and Yannelis (2020) explore the impact of sea level rise and flood risk on the housing market.

I base my empirical analysis on data from the National Flood Insurance Program (NFIP). Kousky, Lingle, and Shabman (2016), Kousky and Michel-Kerjan (2017), Kousky (2018) (among others) describe the program and key characteristics of policy take-up and claims. Wagner (2022) examines reasons for the low take-up of NFIP insurance. Sastry (2021) uses flood insurance limits and changes in flood maps to show how mortgage lenders offload flood risk to the government. Ouazad and Kahn (2021) show how mortgage lenders differentially securitise mortgages across NFIP flood zones. Most closely related to my work is that of Ratnadiwakara (2021), Hu (2022), Xu and Box-Couillard (2024) who investigate how insurance take-up is affected by learning about natural disaster risk via social networks. Relative to these contributions, I focus on adaptation responses and the heterogeneity across households in responses. Outside of the US context, Garbarino, Guin, and Lee (2024) find in the UK that an insurance scheme which subsidises flood insurance for high-risk properties increases house prices and transaction volumes, more than offsetting the effect of higher flood risk.

2 Empirical evidence on responses to flood risk

In this section, I provide evidence on household responses to increased climate risk. There are two main challenges to empirically assessing the aggregate household response to rising climate risk. The first is that there are a wide number of disparate approaches to accommodating risk. To address this, I take a particular case study using US data focused on one of the largest climate risks - flooding[7] - and two major adaptive responses. These examples may not account for the aggregate mitigation of flood risk. Fried (2022) takes an alternative approach, using a calibrated model to infer that aggregate investments in adaptive capital make up 1% of the total US capital stock. Here, however, I use an example from microdata, where the granularity of data covering these specific examples of risk mitigation allow me to understand heterogeneity in household responses. The second challenge is that climate risk is very slow moving, and so does not change substantially within the time horizons of typical administrative micro-datasets, including the National Flood Insurance Program data used here. To accommodate for this, I construct a proxy of flood awareness, using social network data. The aim of the proxy is that household responses to rising climate risk should be similar to the household response to rising awareness of climate risk.

2.1 National Flood Insurance Program and Home Elevation

The National Flood Insurance Program (NFIP) is a government flood insurance provider, introduced in 1968. It grew in prominence after Hurricane Agnes in the summer of 1972 and the subsequent Flood Disaster Protection Act of 1973, which made federally regulated mortgage providers require insurance in high-risk 'Special Flood Hazard Areas'. Flood insurance is provided separately to general homeowners insurance in the US and the NFIP provides over 95% of home flood insurance policies (Bradt, Kousky, and Wing (2021), Kousky (2018)). Flood insurance pricing under the program often does not fully reflect risks. This is partly due to flood maps which can be outdated or imprecise (Michel-Kerjan (2010)) It is also partly due to subsidies and resulting frequent bailouts of the program; Wagner (2022) finds that in high-risk areas, premia charged are only around 2/3 of the expected value of the insurance. Recent legislation on NFIP pricing, including the Risk Rating 2.0 methodology which came into effect in 2022 have helped premia more accurately reflect risks. Despite the subsidisation, uptake of flood insurance is low. As described in Kousky and Michel-Kerjan (2017) and Wagner (2022); in most areas, insurance uptake is below 5%, and even in the highest risk areas, over 40% of households are uninsured. There is also a long-standing limit on flood claims, of \$250,000 for property damage, and \$100,000 for contents.[8]

[7] Flooding is involved in 90% of all natural disasters in the USA, and causes the majority of economic damages (Department of Homeland Security (2024)) This is also true worldwide; for instance, Swiss Re (2022) find that in 2021, flooding caused \$82 billion in economic damages globally, 31% of losses from all perils. In addition, a substantial proportion of the economic damage caused by tropical storms (which account for 33% of damages) are caused by flooding.

[8] The limits on insurance is low compared to the upper tail of property values, but is less binding when you take into account that this only covers the construction value (rather than the land value) of the property, and typically flood damage only causes partial damage to the construction value of the home. As a result,

Elevating homes is a common form of adaptation to flood risk, with a long-standing history in the US.[9] A home is considered elevated by the NFIP if the lowest floor is above ground level, and this is documented for all homes insured by the NFIP.[10] Home elevation can substantially reduce (though not eliminate) risk; floods need to be higher to cause the same level of damage. Kousky and Michel-Kerjan (2017) find that flood claims under the NFIP of elevated homes are 16% lower than non-elevated homes. This lower risk of elevation is reflected in lower insurance premia; Ge, Lam, and Lewis (2022) show that for a high risk, single family home with maximum property insurance coverage, having a property elevated results in premia being just under half that of non-elevated homes. New homes built in high risk (Special Flood Hazard Area) areas are required to be elevated, but because of the age of housing stock, even in these areas only a minority of homes are elevated.

Typically, homes are built elevated or are elevated during substantial renovations. It is also possible to elevate a home retrospectively, by excavating under the structure and raising it. This has a long-standing history; Appendix A shows advertisements for home raising services in 1901, along with examples of present day construction. Retrospective elevation is expensive, and scales with property size. For instance, two case studies registered by FEMA in 2022 relate to the elevation of 24 homes in Houston, Texas for $3.69 million, and 2 homes in Berkeley, New Jersey for $518,216. Once a home is elevated, its elevation record would be different for new flood policies. One way of changing the elevation record of an existing property is to obtain an elevation certificate, which involves a more detailed assessment of the property than that conducted during typical premium pricing.

The National Flood Insurance Program provides administrative microdata on 79.1mn policies taken out. This includes all policies taken out since 2009, along with a partial selection of policies prior to then. I use the vintage of data from mid 2023, and use only 2022 and prior data, to ensure complete years. The data includes a variety of characteristics of the policy, including the location of the property at the census block group level and details

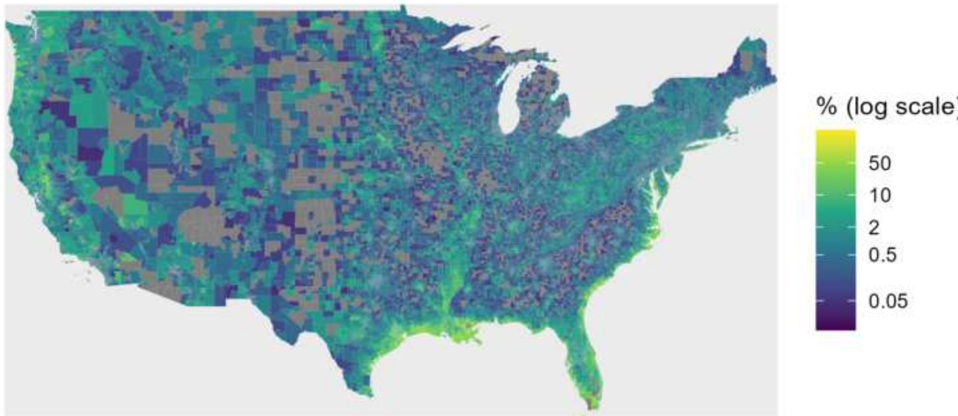
few claims exceed this limit - Kousky and Michel-Kerjan (2017) find that less than 1% of claims reach the property damage limit. In addition, Wagner (2022) finds that only 93% of claims hit the maximum insured value (which is typically below the maximum allowed under the program).

[9]Home elevation is particularly common in the South, around the Mississippi river. New Orleans has a long history of building elevated homes, with architectural styles like the Raised Creole Cottage becoming common in the 19th century - see FEMA (2012)

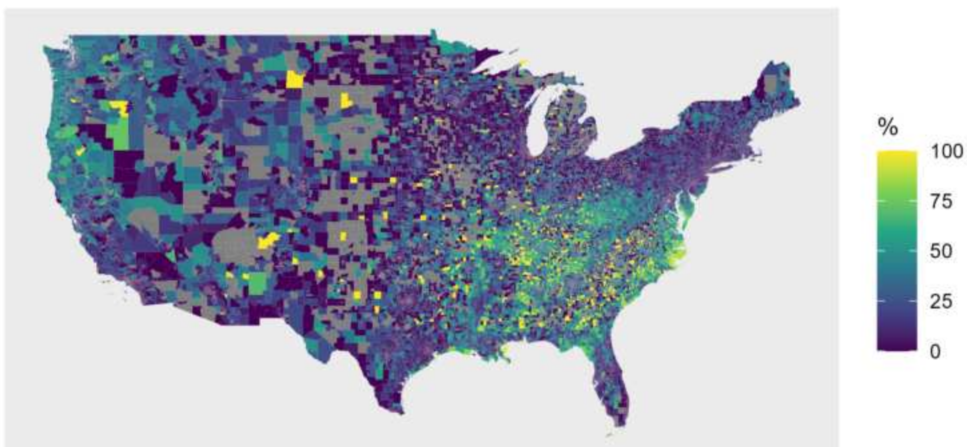
[10]The degree of home elevation is poorly documented in NFIP data (Kousky and Michel-Kerjan, 2017), but the binary variable available for all properties, as it contributes to pricing insurance premia. Formally, the NFIP defines elevation as:

An elevated building is a no-basement building that was constructed so as to meet the following criteria: 1. The top of the elevated floor (all A zones) or the bottom of the lowest horizontal structural member of the lowest floor (all V zones) is above ground level; 2. The building is adequately anchored; 3. The method of elevation is pilings, columns (posts and piers), shear walls (not in V zones), or solid foundation perimeter walls (not in V zones).

Figure 1: Geographic distribution of insurance and elevation



(a) Insured proportion of all housing units

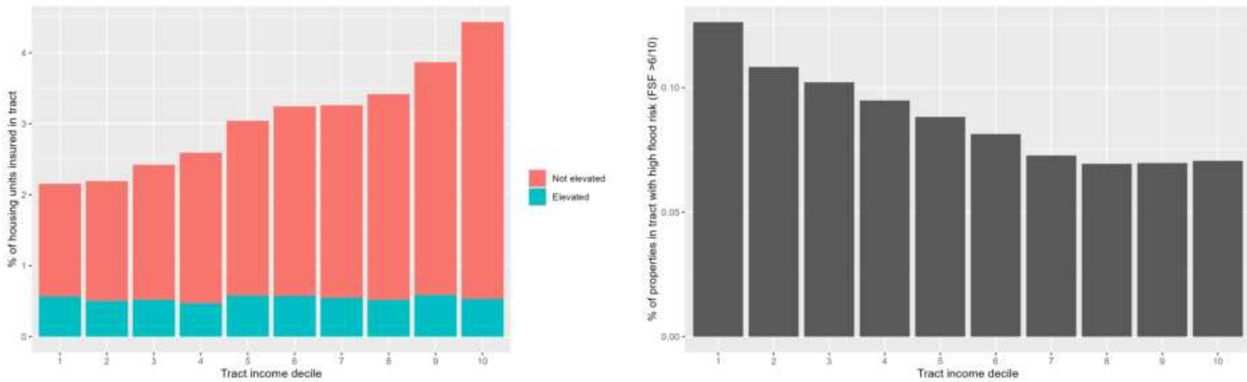


(b) Elevated proportion of insurance policies

Notes: Proportion of homes insured and elevated across census tracts. The insured and elevation proportions are calculated using NFIP data for insurance and elevation totals and ACS data for numbers of housing units (taking the midpoint of the years of ACS sample as the total of housing units in a year).

of the property, including whether the property is elevated. Figure 1 shows the geographic distribution of insurance and elevation. Insurance uptake is typically low, consistent with prior evidence described in Kousky and Michel-Kerjan (2017) and Wagner (2022). Insurance take-up is highest in Florida, along the East coast, Louisiana along the Mississippi basin and gulf coast towards East Texas; all areas typically associated with high flood risk. Elevation is most common amongst insurance policies taken up in eastern states. Appendix Table B.2

Figure 2: Insurance, elevation, and flood risk across the income distribution



(a) Share of properties insured and elevated

(b) Share of high flood risk homes

Notes: Proportion of homes insured, elevated and at high risk of flooding, across tract income deciles. The insured and elevation proportions are calculated using NFIP data for insurance and elevation totals and ACS data for numbers of housing units (taking the midpoint of the years of ACS sample as the total of housing units in a year). High flood risk is defined using FirstStreetFoundation data, where high risk is taken as a score of 6 or more out of 10. Tract income decile is from Census 2000 data, via Opportunity insights.

shows summary statistics for each census tract, the unit of observation.

Figure 2 shows how insurance, elevation and flood risk vary across the income distribution. Overall, insurance uptake is higher amongst higher income census tracts. However, that increase is not made up of both elevated and non-elevated homes. The proportion of elevated homes is fairly constant across the income distribution; only non-elevated homes are increasingly insured at the top end of the income distribution. This lower insurance uptake of lower income areas is despite the fact that lower income areas tend to have higher flood risk, as shown in Panel 2b.

A challenge using the NFIP data is that the data is provided is an unlinked set of policies. If a policy is repeatedly taken out on the same home, this is not explicitly shown in the data. However, for the analysis in this paper, it is important to show the change in insurance and elevation over time. Therefore, I used details of the policies to construct a panel from the data. 90% of flood insurance policies are identified uniquely year-to-year using four variables; the census block group of the policy, date of renewal of insurance policy, original date of policy issuance and date of building construction. For instance, if a property in a specific census block group is renewed repeatedly on 12 April each year, having originally been insured on 12 April 2005, and with original construction date 12 October 1970, then these policies can be linked. For 90% of policies there is only one of each unique combination each year. It is also possible to use further identifying details to ensure these are the same property, but these four appear sufficient. I also link this data with the claims data - all but a negligible (<0.1%) of claims can be matched to their corresponding policies using the characteristics of the property; these I leave out, to omit the effects of insurance claims on subsequent insurance take-up, and particularly, elevation. I use only insurance policies on owner-occupied single family homes, omitting the different dynamics that may be important for buildings with multiple residences or tenancies. This procedure results in an unbalanced panel of 15.4mn repeated policies, with 73.3mn policy x year observations (fewer are used in the main results, as only those with sufficient treatment leads and lags available are used). To create an insurance panel, I assume that for any year where this unique combination of identifying details do not appear, the property is not insured.[11]

2.2 Flood risk awareness proxy

The next component of the analysis is to understand the response of insurance uptake and home elevation to awareness of flood risk. In an ideal setting, one would measure the response of these decisions to actual rises in flood risk. However, given the slow pace of climate change, combined with the shorter time-spans of large administrative micro-datasets like that of the NFIP, there is limited variation in actual climate risk to study. As a result, in this project, I study the responses to changes in climate risk via changes in flood experience across the social network of households.

My proxy of flood awareness will build on a growing recent literature which has shown the importance of social networks as a transmission of information. This is true in a variety of settings, from housing markets (Bailey, Cao, Kuchler, and Stroebel (2018), Bailey, Dávila, Kuchler, and Stroebel (2019)), trade (Bailey, Gupta, et al. (2021)) to responses to the Covid pandemic (Bailey, Johnston, et al. (2024)). It has also been shown to be specifically the case in response to climate change natural disasters; households become more concerned about climate change (Mayer (2023)) and take out more insurance (Ratnadiwakara (2021), Hu (2022), Xu and Box-Couillard (2024)).[12] Intuitively, rare and highly damaging events may be extensively discussed across social networks. In addition, households may have poor understanding of actual flood risk (as suggested by Wagner (2022)), in line with common challenges in understanding low probability events. As a result, communication across social networks has the scope to substantially change households' understanding of risk, and

[11]It could be that a property being purchased results in it appearing the property is no longer insured, because a new original property insurance date appears. This should not affect the results, though, because there would be a symmetric new insurance policy taken out and one newly absent from the dataset. Only if new purchasers were the first to take out a policy, or fails to take out a new policy would this affect the results, but this is one of the changes intended to be found.

[12]Relative to these contributions, I add evidence on investments in adaptation though home elevation, use more granular geographic data and focus on heterogeneity in responses across types of households.

decisions to mitigate risk. I will use the social network data (social connectedness indicator, SCI hereafter) introduced by Bailey, Cao, Kuchler, Stroebel, and Wong (2018), which takes a snapshot of the friendship network from Facebook in 2016.[13]

An important component of the analysis is also to focus not on the response to actual occurrences of floods, but the general rise in flood risk. The response to actual occurrence of natural disasters has been extensively studied in the literature, such as by Deryugina (2017), Deryugina, Kawano, and Levitt (2018), Hsiang and Jina (2014) and Bakkensen and Barrage (2018). However, to understand the extent to which climate damage will rise, it is important to also have measures of the degree of adaptation to reduce the occurrence and extent of damage. This is the focus of this paper. To help with this, my main specification studies the response to flood experience of faraway friends; the parts of the social network above a particular distance from the household. This results in the correlation between flood experience of the household and the flood awareness proxy being close to zero, and more similar to a broad-based rise in risk.

The proxy construction proceeds in three steps: a) recording rainfall at the ZCTA level, b) using the social connectedness indicator to average the flood experience of ZCTA's social network, c) mapping this to census tract geographies, which are recorded in the NFIP dataset. To construct my proxy for flood awareness, I use precipitation data from the Oregon State PRISM project. Precipitation is strongly correlated with flooding, as shown by Pielke and Downton (2000), who argue that climatically defined floods often are less predictive of economically damaging flooding than precipitation measures.[14] Precipitation also has the advantage that it is available at a very granular geographical level and not endogenous to the existing degree of adaptation, unlike flood realisations. It may also result in concerns about flooding within the social network, even when precipitation events are not extreme enough to cause flooding. I use annual average precipitation measures at a 4km resolution, produced using climatologically-aided interpolation. As the next stage of the analysis is at the ZCTA geography, I take the area-weighted average of this measure for each ZCTA. As a robustness check, in Appendix C I also report results using the number of extreme local precipitation days, recorded by the CDC's National Environmental Public Health Tracking data service.

I then combine this data with the Social Connectedness Index (SCI) introduced by Bailey, Cao, Kuchler, Stroebel, and Wong (2018). I use the SCI at the US ZCTA to ZCTA code level, which was first introduced by Bailey, Farrell, Kuchler, and Stroebel (2020). The proxy

[13] I will use a single snapshot of the friendship network for the whole period of analysis, rather than a time-varying measure, given evidence that the friendship network is relatively time invariant.

[14] They find that the number of 2-day heavy precipitation events is the most strong predictor of damaging flooding, but total precipitation which is used in my main analysis is only marginally worse and is available with considerably more geographic granularity.

measure, the average rainfall experience of an area i in year t is calculated by averaging the rainfall in friend's zipcodes j:

$$\text{Friend rainfall}_{i,t} = \sum_{j=1}^{J} \text{SCI}_{i,j} * (\text{rainfall})_{j,t} \tag{1}$$

I restrict this average to only the friends zipcodes j which are more than 200 miles away from the area i, to limit the correlation with local weather events. Finally, I map from ZCTAs to census tracts using the Census Bureau's 2010 ZCTA to census tract crosswalk, taking the average of the proxy measure across all ZCTAs intersecting with a given census tract. In the main results, I show the response to the log of this variable, normalised by its standard deviation.

2.3 Empirical specification

I use an event study to understand how insurance take-up and home elevation respond to the proxy for flood awareness, described in the previous section. I use a standard two-way fixed effects specification, following Freyaldenhoven, Hansen, Pérez Pérez, and Shapiro (2021). The outcome of interest is $y_{i,c,t}$, typically a binary variable for whether or not a home is insured or elevated. This is observed for an individual property i in census tract c, in year t. I assess the dynamic responses to changes in the proxy for flood awareness, $z_{c,t-k}$, constructed for the census tract c and year t at lag k, which is a continuous variable. I include property and yearly fixed effects, α_i and γ_t. The baseline specification is:

$$y_{i,c,t} = \sum_{k=-(K-1):-2,0:(M-1)} \delta_k \Delta z_{c,t-k} + \delta_{-K} z_{c,t+K} + \delta_M z_{c,t-M} + \alpha_i + \gamma_t + \varepsilon_{i,c,t} \tag{2}$$

I cluster the SEs by year and census tract, at the treatment level. The sample period for the analysis is 2009-2017. I use lag length $K = M = 5$ for the insurance results, and extend this to $K = M = 6$ for the home elevation results. The latter choice is to reflect that home elevation is a more substantial and potentially time-consuming change to make.

In addition to this, to understand heterogeneity across types of households, I further interact the treatment variable with a dummy variable Inc_c which reflects whether the income in the census tract is above or below the median across all census tracts. The variable I use for income is the mean household income for the census tract, from the 2000 Decennial Census, via Opportunity Insights (Chetty, Friedman, Hendren, Jones, and Porter (2018)). This interaction is a fixed value taken prior to the sample, so before the effects of the flood awareness proxy. The interacted regression is:

$$
\begin{aligned}
y_{i,c,t} = &\left(\sum_{k=-(K-1):-2,0:(M-1)} \delta_k^L \Delta z_{c,t-k} + \delta_{-K}^L z_{c,t+K} + \delta_M^L z_{c,t-M} \right) \times \mathbf{1}(\text{Inc}_c = 0) \\
&+ \left(\sum_{k=-(K-1):-2,0:(M-1)} \delta_k^H \Delta z_{c,t-k} + \delta_{-K}^H z_{c,t+K} + \delta_M^H z_{c,t-M} \right) \times \mathbf{1}(\text{Inc}_c = 1) \\
&+ \alpha_i + \gamma_t + \varepsilon_{i,c,t} \quad (3)
\end{aligned}
$$

Where δ_x^L, δ_x^H are the effects for low and high income areas, respectively. As the areas are census tracts, and so fairly granular, then absent very high inequality it is perhaps reasonable to interpret these responses as the typical responses of high income households. Here, the specification is estimated to give the level of treatment effect of the two groups; one alternatively could estimate a difference between the groups.

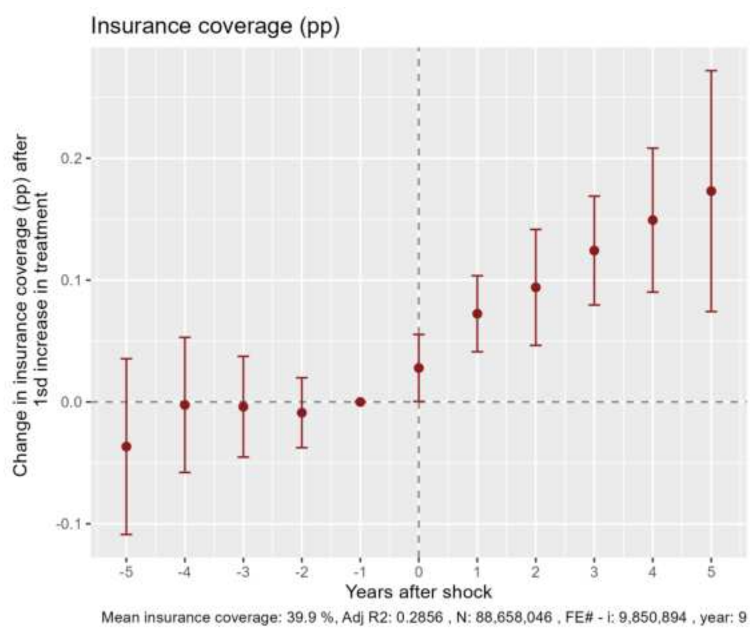
Given that rainfall experience within a household's social network would not be directly affected by insurance take-up and home elevation, the δ coefficents should be able to be interpreted as causal effects of flood risk awareness on these household decisions. The key threats to this interpretation are twofold. The first is that the proxy does not actually correspond to awareness in flood risk. This might be because the information is not transmitted across the network or not interpreted by households to change their understanding of their own risk. My results in the following section are hard to square with this interpretation. A second concern is that the channel of transmission could be confounded by other channels. A varied literature has found that rainfall has a variety of effects on economic outcomes, or alternatively it could be that the social network is correlated with other economic networks (such as that of domestic trade patterns, see Bailey, Cao, Kuchler, Stroebel, and Wong (2018)). My assumption is that indirect effects via other economic channels would be a much more minor driver of changes in insurance and elevation decisions; households would be more likely to insure more because they were aware of risk, rather than a economic spillover via trade networks causing a marginal change in income.

Another concern could be identification issues due to the network nature of the proxy construction. The combination of (exogenous) rainfall and (potentially endogenous) social network suggests that my identification strategy could be subject to omitted variable bias of the type described by Borusyak and Hull (2020). They recommend controlling for a measure of average treatment across shock counterfactuals, to address this. However, they also note that in panel data, unit fixed effects can purge this bias when the expected instrument is time invariant. If rainfall is modelled in a simple way, such that this is satisfied, then the fixed effects in my specification should avoid this issue. This is potentially a reasonable assumption given the short time-span of my analysis. However a more complex time-varying model of rainfall could be used with their approach could assess if this is the case.

2.4 Results

In this section I show how a rise in flood awareness significantly increases both insurance take-up and home elevation. I further show how there is substantial heterogeneity in responses, suggestive of the inability or unwillingness of low income households to make larger, long-term investments in adaptation. I finally present results showing how my results are robust to considering other channels, like migration, and different data construction choices.

Figure 3: Insurance - Response to flood salience shock



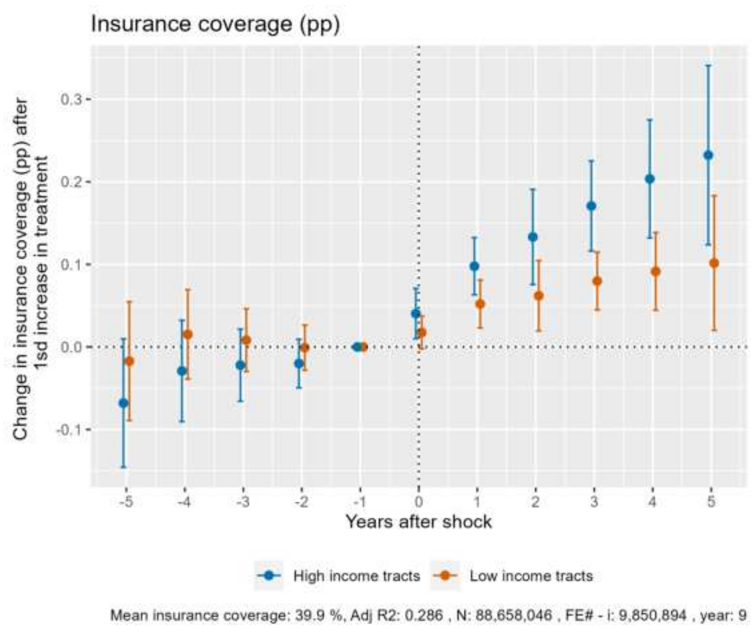
Notes: Response of insurance take-up to the flood awareness proxy, using specification 2.

In response to a rise in flood awareness, Figure 3 shows that insurance uptake rises significantly. In response to a 1 standard deviation rise in the flood awareness proxy, insurance uptake rises by 0.1pp after 2 years. This is relative to a baseline mean insurance uptake of 39.9%,[15] consistent with this being a likely small change in awareness of and concern about flooding. The effect increases to just over 0.15bp by 5 years after the shock. The fact that the point estimate of the treatment effect continues increasing is somewhat surprising; it might

[15]The average insurance coverage in the sample is substantially higher than average flood insurance take-up, as the data only includes homes which, at some point during the sample, have taken out insurance. Other homes are unobserved in the data.

be more reasonable to become more constant or even diminish over time, after the shock. One explanation for the persistence could be that a chance, temporary rise in the flood awareness proxy results in more attention to climate change. Given that climate change is a long-term and increasing concern, this could suggest a permanence in learning about risks, and that the shock is successfully mimicking responses to broader awareness of climate risks rising. In addition, the final estimate, for five years after the shock, is not significantly different from any of the lags at 2-4 years. Finally, leads of the shock suggest there are no pretrends or anticipation of the flood awareness shock. Taken together these results are consistent with the flood awareness shock resulting in more concern about flood risks and households making decisions, by taking up insurance, to insulate themselves against this risk. The results also validate similar results from Ratnadiwakara (2021), Hu (2022) and Xu and Box-Couillard (2024).

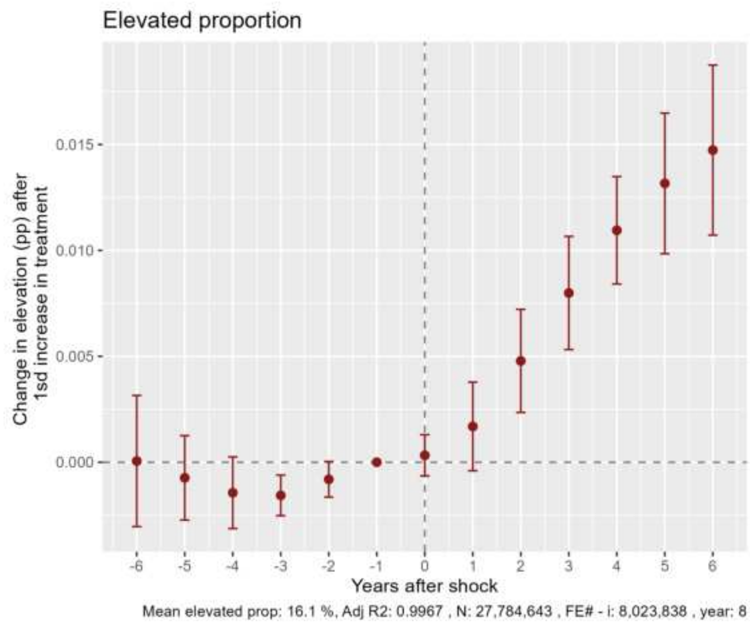
Figure 4: Insurance - Heterogeneity in response to flood salience shock



Notes: Response of insurance take-up to the flood awareness proxy, using specification 3.

While Figure 3 suggests that the flood awareness proxy increases insurance take-up, Figure 4 shows there is some heterogeneity across types of households. This shows the effect of the flood awareness proxy in low income and high income areas, using specification 3. Households in high income census tracts respond more to the flood awareness shock. The insurance take-up is about double in high income areas, and significantly over most of the period following the shock. The heterogeneity could be due to a different degree of information transmission or greater concern and response to the information being transmitted. It is challenging in this setting to distinguish between these two channels. However, if a household receives the information, and makes different decisions on insurance compared with home elevation, that would indicate the latter channel; different responses, rather than different information acquisition. As a result, I will focus on relative responses between the two income groups and their decisions on insurance versus home elevation.

Figure 5: Elevation - Response to flood salience shock

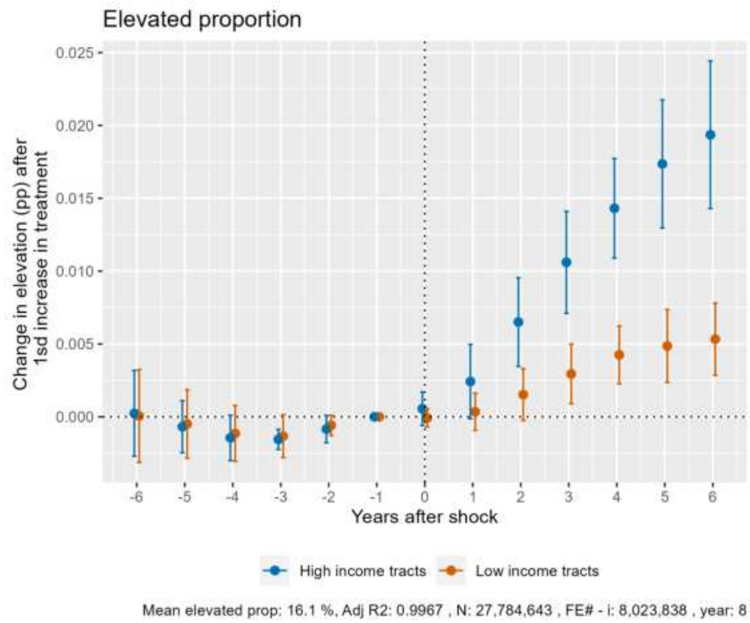


Notes: Response of elevation to the flood awareness proxy, using specification 2.

Overall responses of home elevation to the flood awareness shock are shown in Figure 5. In a similar manner to insurance take-up, after the flood awareness shock, households increasingly elevate their homes. Because of the way the data is constructed, described in Section 2.1, these results reflect changes for a particular home. They avoid reflecting selection into the sample, for instance if owners of elevated homes were more likely to begin insuring their homes after the shock. There is a strongly significant, 1.5bp increase in the proportion of homes elevated by 6 years after the shock. The average elevated proportion of homes in the sample is 16.1%, so this is an economically small increase, similar to the insurance response, reflecting the small change in information and concern about flood risk. The size and speed of the response is slower for home elevation than insurance, reflecting that changing home elevation is a much more expensive and time-consuming process (as outlined in Section 2.1). The response to leads of the flood awareness proxy in the pre-trends are mostly insignificant, other than 3 years before the shock.

The heterogeneity in home elevation responses are given in Figure 6. This shows one of

Figure 6: Elevation - Heterogeneity in response to flood salience shock



Notes: Response of elevation to the flood awareness proxy, using specification 3.

the key findings; high income households are relatively much more likely to adapt in response to rising risk. The figure shows that households in high income areas increase the elevation rates by 0.02pp by the end of the horizon. This is 4 times the size of the response of low income areas, which increase elevation rates by 0.005pp. Comparing this with the insurance take-up results in Figure 4, there is much more heterogeneity in elevation responses; 4 times larger for elevation in high income areas, compared to 2 times larger insurance responses. Therefore, while rich households respond more in absolute terms to the flood awareness shock - whether due to greater information transmission or greater concern about risk - they are also much more relatively reliant on adaptive investments to absorb risk.

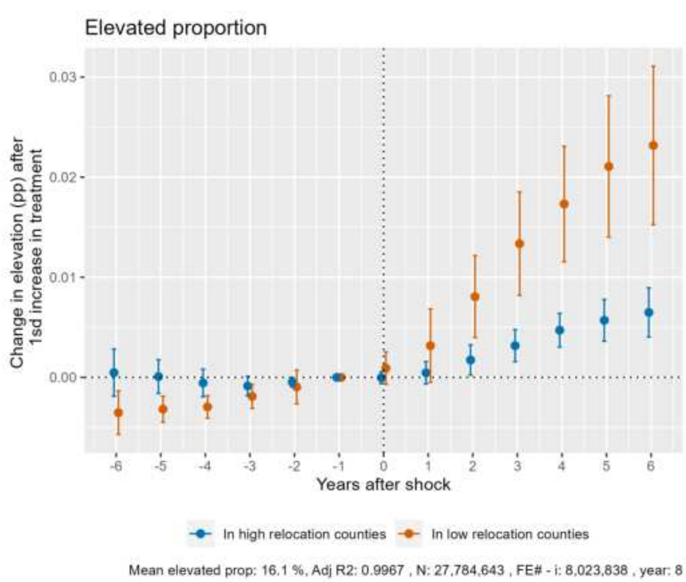
Mapping empirical results to the model I aim to use these empirical results to quantitatively evaluate the model in the next section, where I model a much more substantial, permanent rise in flood risk. I assume, in doing this, that the household responses to the perceived and actual transmission of risk are similar. The size of the shock, given the nature of its construction, naturally results in small responses of both elevation and insurance. Given this, to evaluate the model responses, I will focus on the *relative* responses of insurance compared to elevation. Overall insurance rates respond approximately 14 times than elevation, four years after the shock. In comparison, the relative response of insurance is 25 times for low income areas, and 13 times for high income areas.

2.5 Robustness

In this section I detail a number of further empirical results and robustness checks. I first show how the results in the previous section are primarily driven by areas with low levels of relocation. Next I show how the results are robust to different choices on flood awareness proxy construction.

Relocation One key alternative long-term adaptive response to rising climate risk is to relocate to areas which are less at risk. Bilal and Rossi-Hansberg (2023) explore this in detail; they find empirically that the realisation of large storms and heat waves reduce local populations, and that migration responses mitigate the degree and geographical heterogeneity of welfare losses from climate change. How effective migration is as an adaptive mechanism will depend on non-climate risk motivations for relocation, however. Currently projected demographic shifts suggest that the US population is relocating to areas with higher flood risk - for instance, for the amenity values of living in coastal areas - compounding climate related increases in risk (Wing et al., 2022). In this section, I extend the main results to explore how migration might interact with physical adaptive investments.

Figure 7: Elevation response - low vs high migration areas

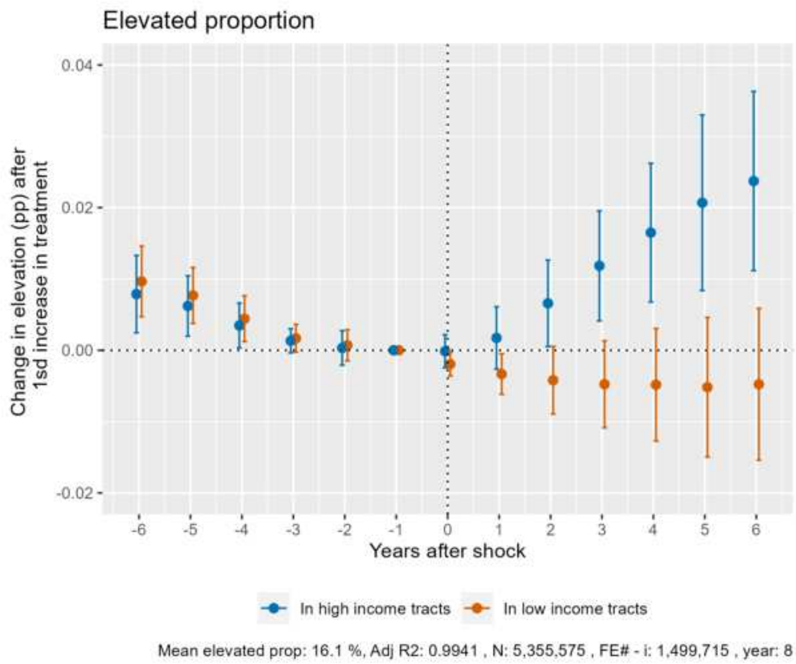


Notes: Response of elevation to the flood awareness proxy, using specification 3, where the interaction variable is household relocation, using county level ACS data, as described in text.

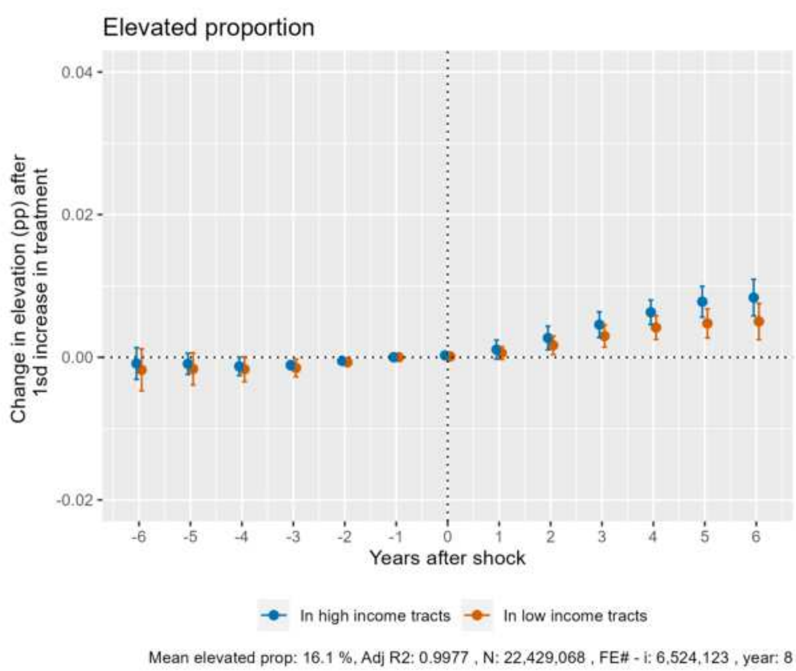
As flood risk can be very localised, my main measure of relocation is also local. I measure this using the American Community Survey's Migration Flows data, taking the number of movers - those who live in a different residence to the previous year - as a proportion of the population. This is available at the county level. I use the 2006-2010 ACS, so that the majority of the relocation responses have occurred prior to the sample period used in the event study. I split counties into two groups; 'high relocation' and 'low relocation' counties, based on whether these shares are above or below the median across all counties. These areas are largely similar other than the level of relocation.[16]

[16]Appendix Table B.1 shows that these areas are similar in key economic observable characteristics, other than the share of rural areas. Rural areas tend to have much lower relocation rates. This suggests that any differences may be driven primarily by this characteristic, rather than other correlated characteristics

Figure 8: Comparison of low and high migration areas, split by income group



(a) Low relocation areas



(b) High migration areas

Notes: Response of elevation to the flood awareness proxy, using specification 3. The interaction variable is relocation at the county level, using ACS data on the proportion of households moving housing, as described in text.

Figure 7 shows the response of home elevation, split into these two types of areas. Low relocation areas are much more likely to respond by elevating their homes. This is consistent with the scenario where those who are committed to staying in their homes long-term being more willing to elevate their homes. Those who are more likely to relocate may not personally value the reduced risk in the long-term, particularly if the reduced risk brought about by elevation does not result in higher house prices. In the Appendix, Figures B.1 and B.2 show corresponding results for insurance take-up, and alternative relocation measures.

Figure 8 further splits each group into high and low income tracts. This shows that the aggregate increase in home elevation is driven by areas which are both high income and have low relocation rates. Low income, low relocation rate areas do not increase their elevation. In addition, in high migration areas, there is minimal change in home elevation and the heterogeneity across income levels is also small. This evidence is consistent with the main mechanism I suggest in the paper; those with longer planning horizons, because they are both less financially constrained, and also planning to remain in their home long-term, are the most likely to make adaptive investments.

Different shock construction The main results use a specific flood awareness proxy. To show that the main findings are not dependent on these decisions, in Appendix Section C there are results using different approaches to constructing the flood awareness proxy.

Firstly, I construct the flood awareness proxy using the count of extreme rainfall days, rather than average precipitation. The results are shown in Figures C.1 and C.2. This data is taken from the CDC's National Environmental Public Health Tracking data service, measured at the year by census tract level. Pielke and Downton (2000) find that these counts of daily extreme precipitation aren't a stronger predictor of economically damaging floods, and shows that typically measures of extreme precipitation are strongly correlated with average precipitation. The broad findings are similar; insurance and elevation rates both rise following the shock, with high income households more substantially increasing their elevation rates. There are slight signs of pre-trends in these results, however.

Similarly, I also construct an alternative flood awareness proxy using the county of flood insurance claims, rather than precipitation. These results are shown in Figures C.3 and C.4. Flood claims are potentially less exogenous to broader trends in flood awareness than average precipitation in an area. For instance, if a social network had other reasons which led to a greater understanding of flood risk, that might result in higher insurance uptake within the friendship network prior to the flood event. This would result in more flood claims than otherwise would be the case. In this case, the 'shock' of the flood in the friendship network would be confounded with the prior increasing flood awareness. This may well be the case here; the post-treatment findings are similar, but there are substantial pre-trends prior to the event date.

Next, I show the rationale for using far-away friends, rather than the full friendship network or local flooding. The reason for the exclusion local rainfall in the baseline results is that confounding economic effects of floods might affect the results; for instance, damage to local labour markets or short-term migration following a flood. As a large portion of the friendship network is nearby, this leads the flood awareness proxy constructed using the full friendship network to be strongly correlated with local precipitation. Figures C.5 and C.6 show the results including the full friendship network, and Figures C.7 and C.8 show the results for response to local tract flooding, using the same PRISM data as the flood awareness proxy. These results suggest that confounding effects may well be at play. Insurance take-up does not significantly increase, and the proportion of elevated homes falls substantially. Both results also show substantial pre-trends.

Other specifications and results Appendix Figures C.9 and C.10 show results where the regressions are run at the aggregated, census tract level. The results similar; insurance and elevation proportions rise, with high income households' proportion rising more. These results have the downside of not being able to focus on individual responses. This means that changes in the elevated proportions of houses may reflect *either* changes in elevation, or changes in the type of homes that are insured. The elevation responses are somewhat attenuated and less heterogeneous, which may reflect that low-risk homes are more likely to be insured following the shock.

Finally, Appendix Figures C.11 and C.12 show the response to increases in cost of insurance. These are complementary to innovative approaches to estimate the elasticity of demand for flood insurance by Wagner (2022), among others. I estimate the response to a residualised increase in insurance costs, which are not explained by property characteristics, flood risk and time of policy issuance. The remaining change in cost is primarily driven by risk-specific changes in insurance premia pricing over time, as the NFIP's pricing policies have changed. I find that insurance take-up falls when prices increase, as expected. In the aftermath of this change, high-income areas see an increase in elevation, whereas for low income areas the change is very small. This echoes the responsiveness of high income areas' elevation to flood awareness. See Section C for further details and discussion.

3 A model of household responses to rising risk

The empirical analysis suggests considerable heterogeneity in households' responses to rising awareness of climate risk. In order to draw broader conclusions from this, in this section I outline a heterogeneous agent macroeconomic model. The objective of this exercise is two-fold. Firstly, the prior evidence focussed on individual responses of insurance and elevation only. Using this macroeconomic model can incorporate this evidence, but also assess broader aggregate and distributional consequences of these decisions. Secondly, the prior evidence was on short-term shocks to awareness of climate risk; risk did not actually impact households. One of my key assumptions is that the long-run responses to actual rising climate risk will display similar micro-level responses of households; eventually households will become more aware of this risk, and act similarly to when risk levels remain the same and only their awareness is changed. The model, however, allows me to simulate the economic responses to a slow increase in actual climate risk. This gives an understanding of the response of aggregate consumption, housing and - crucially - aggregate economic damage suffered as a result of rising risk.

In this section, I first outline the approach to modelling household decisions to mitigate climate risk. I build on a standard Huggett economy,[17] where households decide to consume, save and borrow in risk free bonds, in the face of idiosyncratic income risk and borrowing constraints. Onto this framework, I add a decision to invest in housing. Housing brings utility, but is an illiquid investment, in the spirit of Kaplan, Moll, and Violante (2018). Housing investments are further subject to occasional disaster risk, on realisation of the flood. Households can choose to take out insurance or elevate their homes to mitigate this risk.

This framework is designed to capture the intuition of household constraints shortening financial planning horizons and reducing incentives to mitigate risk. An extensive literature has explored how households with idiosyncratic income risk and borrowing constraints may not act as a representative household without these distortions; the borrowing constraint distorts their Euler equation. Households which are close to their borrowing constraint might care less about investing to avoid risk that is rising over a long-term horizon. This is similar in spirit to McKay, Nakamura, and Steinsson (2016) and McKay, Nakamura, and Steinsson (2017), where incomplete markets result in heavier discounting of future interest rate changes, reducing contemporaneous effects of forward guidance. Other mechanisms which lead to different discounting of the future; different preferences or behavioural frictions could also play a role. To the extent that other factors that may result in a shortening of planning

[17] In the spirit of Bewley (1980), Imrohoroğlu (1989), Aiyagari (1994), and Huggett (1993)

horizons are also correlated with income these other factors may play a complementary role; empirical strategy does not explicitly distinguish between them.

Households There is a continuum of infinitely lived households, who gain utility from consumption and housing, with preferences:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[u(c_t) + \gamma u(H_t)\right]$$

where c_t is consumption of an individual household at time t, H_t is the housing consumed in period t. $u(.)$ has a standard constant relative risk aversion form, $u(.) = \frac{(.)^{1-\sigma}}{1-\sigma}$. Households have labour productivity s_t, which is an exogenous idiosyncratic process. Log productivity follows an AR(1) process with persistence ρ_s and variance σ_s:

$$log(s_t) = \rho_s log(s_{t-1}) + \epsilon_t \tag{4}$$

This is approximated by a Markov process using the Rauwenhorst method, and combined with aggregate wage w gives households labour earnings $w_t s_t$ in each period. Households can borrow and save in a risk-free bond b_t, which is subject to a borrowing constraint $b_t \geq \underline{b}$.

Housing and climate damage Households invest in and get utility from housing. Housing is a continuous variable, h, with price p^h and depreciates at rate δ. Households get utility from their housing stock in the period after they choose it. After they choose their housing stock, the housing may damaged by a flood. The flood is represented which is a binary exogenous state f which is an iid process, occurring with probability ρ^f. If a flood occurs, it reduces the value of the house by a fraction τ^f, which reduces both the utility that is enjoyed from the house in the subsequent period, and its financial value in the budget constraint.

Housing is an illiquid asset, subject to kinked and convex adjustment costs. This illiquidity is in the spirit of evidence from Kaplan, Violante, and Weidner (2014) and use in Kaplan, Moll, and Violante (2018), and allows high wealth agents to still be hand-to-mouth if their wealth is held in illiquid assets. Here, the specification of adjustment costs is as in Auclert, Bardóczy, Rognlie, and Straub (2021) (included in Appendix D).

Elevation The first option to mitigate risk from flood damage is for households to choose to adapt their housing using elevation. This is modelled as a binary state $e \in \{0, 1\}$. If a home is elevated, the damage from flooding is reduced by fraction τ^e. The downside of elevating is that elevated homes are priced at a premium, so the per unit cost of an elevated home is $p^h + p^e e$. In addition, the investment in elevation is also illiquid; changing elevation status comes with a adjustment cost, which is linear in the amount of housing:

$$\Phi^e(e', e, h) = \chi^e \mathbb{1}(e \neq e')H$$

This adjustment cost represents two ways of changing the elevation of a home; either i) the cost of renovations to elevate homes, or ii) the adjustment cost of moving between similarly sized homes with different elevation rates. Note that in this set-up, elevation is not an absorbing state; it is possible to move from an elevated to a non-elevated home or renovate an elevated home to a non-elevated home[18]. The resulting amount of housing H which is held in the period after the housing decision and after the realisation of the flood shock is given by:

$$H(h, f, i, e) = (1 - f * \tau^f(1 - \tau^e e))(1 - \delta)h$$

Insurance To reduce the financial damage of flooding, households can choose to purchase insurance $i \in \{0, 1\}$, either full or no coverage.[19] If taken out, in the aftermath of a flood event, households receive a payout equal to the financial value of the flood damage to their homes. It does not, however, mitigate the damage to utility in the period after a flood occurs; intuitively, the household still has to live in the damaged house for a period, but is given a transfer to rebuild and compensate for the financial loss. Insurance can be taken out on both elevated or non-elevated housing. Insurance premia are priced at a potential discount or subsidy q compared to the expected fair value of the insurance, per unit of housing $\rho^f \tau^f(1 - \tau^e e)(p^h + p^e e)$. Taking this together, the net payment from insurance each period is given by:

$$I(h, f, i, e) = i(\underbrace{f\tau^f(1 - \tau^e e)(p^h + p^e e)}_{\text{Insurance payout}} - \underbrace{q\rho^f \tau^f(1 - \tau^e e)(p^h + p^e e)}_{\textit{Premium}})(1 - \delta)h$$

In addition to these features, I also add a utility cost to insurance. This aims to capture the findings in Wagner (2022), among others, that US flood insurance uptake is surprisingly low, perhaps reflective of non-pecuniary costs or behavioural frictions. This element is important

[18]The empirical evidence primarily reflects the former example, the actual renovation of a home to being elevated. In the data, around a third of changes in elevation are from an elevated home to a non-elevated home.

[19]Insurance is modelled as a binary choice; either full insurance is taken out, or no insurance is purchased. Partial coverage is not allowed for. This matches the binary evidence from the empirical section. It is also consistent with typical behaviour in the US flood insurance market, where coverage purchased typically covers the full reconstruction value of a home (see e.g. Turner and Landry (2020)).

to allow the model to match the low uptake of insurance seen in the data. I model this cost as proportional to lifetime utility, to keep the incidence of this cost similar across the distribution.

Timing and full household problem Within a period, households first choose to insurance i and elevation for the next period e'. There is then the realisation of the exogenous states, s, f. After the realisation, households decide their investment in housing h', consumption c and saving b'. The value function of the household is given by:

$$
\begin{aligned}
V(b,h,i,e;s,f) = \max_{b',h',i',e'} \{ & u(c) + \gamma^H u(H(h,f,i,e)) - \gamma^I i V(b,h,i,e;s,f) \\
& + \beta\, \mathbb{E}[V(b',h',i',e';s',f')] \}
\end{aligned}
$$

Subject to:

$$
\begin{aligned}
& c = ws + (p^h + p^e e)H(h,f,i,e) + (1+r)b - \Phi^H(h',h) - \Phi^E(e',e,h) \\
& \quad - (p^h + p^e e')h' - b' + I(h,f,i,e) \\
& b' \geq \underline{\mathrm{b}}
\end{aligned}
$$

Appendix D gives further details of the household problem, including the envelope conditions, first order conditions, and details of the solution approach. I split the household problem into a series of stages, which aids the solution for discrete choice problems, as outlined by Druedahl (2021) and use the toolbox of Auclert, Bardóczy, Rognlie, and Straub (2021).

Equilibrium My approach to equilibrium in this model is to treat the economy as a open, local endowment economy, representing the part of the US economy (say, Florida, the east and gulf coasts) which is particularly affected by flood risk. I take the interest rate as exogenous and allow the households to borrow and save from the rest of the rest of the country. I solve for house prices p^h to solve local housing market equilibrium. I assume that there is a fixed stock of housing, HS, which can be thought of as a fixed stock of land. I solve for house prices which allow the total housing demand of households to equal this housing supply, $HS = \sum_j h'_j$. The payments households make against flood damage and depreciation can be thought of as maintenance payments to keep the housing stock constant. One could also extend this to have segmented housing markets, so that the premium on elevated homes is time-varying, for instance if there was congestion in the demand for construction companies to elevate homes. This is one aspect I hope to explore in future versions of the paper. In practice, the proportion of the construction market needed to elevate homes is likely small compared to the overall construction sector, plus the change in total elevated housing stock is small in the current set of results, so this is unlikely to change the results substantially.

3.1 Calibration

Table 1: Model Calibration

Parameter	**Value**	**Description**
β	0.96	Discount rate
$1/\sigma$	2.5	Intertemporal elasticity of substitution
p_h	1	Price of housing
c_e	0.15	Cost of elevation
w	1	Wage
τ^e	0.5	Damage reduction from elevation
q	0.7	Insurance subsidy
γ^I	1e-6	Disutility from insuring
ρ^f	0.01	Flood risk
τ^f	0.25	Flood damage proportion
r_b	0.02	Bond return
δ	0.025	Depreciation of housing
χ_0	0.25	Housing adjustment parameter
χ_1	0.9	"
χ_2	1.2	"
χ_e	0.01	Elevation adjustment
γ^H	0.1	Housing utility
ρ_z	0.966	Persistence of productivity shocks
σ_z	0.92	Variance of productivity shocks
$\underline{\text{b}}$	0.1	Borrowing constraint

The calibration of the model is summarised in Table 1. My intention with this model is to approximate local areas of the US economy which are at a particularly high risk of floods. As such key elements of the calibration are chosen to fit the US flood insurance data, which most heavily taken out is taken out in high flood risk areas. The initial starting steady state of the model is calibrated to have a 1 in 100 year flood risk, the cut-off risk level to be considered a Special Flood Hazard Area in the US.[20] The damage from floods is calibrated to 25% of building value, following evidence from Kousky and Michel-Kerjan (2017) using

[20]In addition, Wing et al. (2022) find that the overall average annual exposure of the US population to flooding is 1.18%, similar to this calibration.

NFIP flood claims. Note that this is as a proportion of the building's construction value, rather than the total value of the property.

I use a typical insurance subsidy of 30% below fair value, consistent with the evidence from Wagner (2022) that flood insurance is priced around 30% below realised average cost. In addition to this, a utility cost of 1e-6 of lifetime utility is imposed when taking out insurance, in order for insurance take-up to be consistent with the low rates in the data.[21] Elevation is taken to reduce the damage of floods by 50%. This is somewhat higher than the 16% lower flood claims of elevated homes in Kousky and Michel-Kerjan (2017), as the latter does not include the fact that many elevated homes would not suffer damage after a flood, and so the probability of making a claim is lower. A higher flood protection also seems necessary for the model dynamics to fit the empirical evidence. The cost of elevation is 15% of the house value, which is consistent with the cost to elevate a home to base flood elevation level (a less than 1 in 100 year risk) for examples used in Xian, Lin, and Kunreuther (2017), as a proportion of building value. The cost of home elevation is highly heterogeneous, but tends to increase with square footage of the house, which this simple linear method of home elevation cost captures. In addition to this, the cost of elevation depends a wide range of factors, including the nature of elevation method and number of floors, see FEMA (2020) for a detailed discussion of methods.

The initial steady state price of housing is normalised to 1, equal to the price of consumption. The housing adjustment parameters included in the table are chosen to give a similar adjustment cost function calibration to that of Kaplan, Moll, and Violante (2018), with slightly less convexity. The elevation adjustment cost is set to 1% of the housing choice, which results in 13% percent of households adjusting their elevation choice each period. The utility parameter from housing, γ is set to 0.1, which results in a housing to consumption ratio of approximately 0.35 - relatively low. This element of the calibration is a crucial one I would like to improve in future versions of the paper. Currently, there is a conflict with the evidence, where a higher housing demand typically results in much higher insurance and elevation proportions than seen in the data. The current calibration is a compromise between these issues. One extension to the model which could address this is to more explicitly consider the role of mortgages. Van der Straten (2023) makes an excellent contribution to the literature exploring the role of mortgages in homeowners' response to flood risk. As households purchase homes outright, to an extent, the current model set-up reflects the housing equity held by households, rather than the total value of housing, hence the low housing

[21] As highlighted by Wagner (2022), the willingness to pay for insurance is markedly low, and potentially consistent with some non-pecuniary costs or behavioural frictions preventing take-up of insurance. This utility cost aims to capture this.

to consumption ratio. Homeowners in practice are likely to be leveraged, which could be reflected in a higher 'price' of elevation and insurance, to the extent that homeowners are having to personally pay to elevated and insure to reduce the risk to the portion of housing value which is mortgaged. Alternatively, an extension to mortgages could address this issue, and also potentially help match the MPC in the model to that seen in the data.

The aggregate wage is set to 1, and the persistence and variance of productivity shocks are 0.966 and 0.92, consistent with the values used in the two asset model of Auclert, Bardóczy, Rognlie, and Straub (2021). The productivity process is approximated by a Markov chain using the Rouwenhorst method. I use a discount rate of 0.96. The intertemporal elasticity of substitution is 2.5 which is higher than typical values used in the literature. The lower risk aversion which this implies is needed for households to be willing to hold housing assets that are exposed to flood risk, in a manner similar to that in the data. The risk-free return on bonds is 2%. Numerical parameters used for the solution method are shown in Table D.1 - of note, the variance of taste shocks used for solving the discrete choice decisions is chosen so that these are sufficiently small to not affect the aggregate proportions of elevation or insurance.

3.2 Results

The empirical evidence in Section 2 shows the micro responses of insurance and elevation to rising flood awareness. The model simulation aims to match the empirical evidence qualitatively and allow an broader understanding of what this implies for macro outcomes and how climate damage affects different households. Using the model outlined in the previous section, I simulate the response to a rise in flood risk - assuming that the prior empirical exercise approximates this. Because of the challenge of comparing the magnitude of the flood awareness shock with the actual flood risk rise in the model, I will primarily qualitatively compare the model and empirical results.

Table 2 summarises some key elements of the initial steady state, given the calibration in Table 1. To complement this table, in the Appendix, Figures D.2 and D.3 show example policy functions, average decisions and the distribution of households across bond and housing states. Households spend most of their labour earnings on consumption, with a relatively low share spent purchasing and repairing the housing stock. Income inequality driven by the idiosyncratic risks to productivity results in inequality in consumption and housing, as expected. To keep the comparison with the empirical results, I split the income distribution in two; above and below median. Low income households have lower consumption and housing, as expected.

Households in aggregate borrow from the rest of the economy, with lower income households being more likely to be at the borrowing constraint. The marginal propensity to consume is 0.066 - lower than typical estimates in the literature of around 1/3 (e.g. Johnson, Parker, and Souleles (2006)). This reflects that households are able to use their savings in housing wealth to smooth consumption, in addition to bonds. A higher adjustment cost might increase the MPC and this accompanied by higher utility from housing and a higher housing stock, as mentioned in the previous section, might allow a better match to the US economy and I aim to explore this in future versions of the model.

Table 2: Steady state outcomes

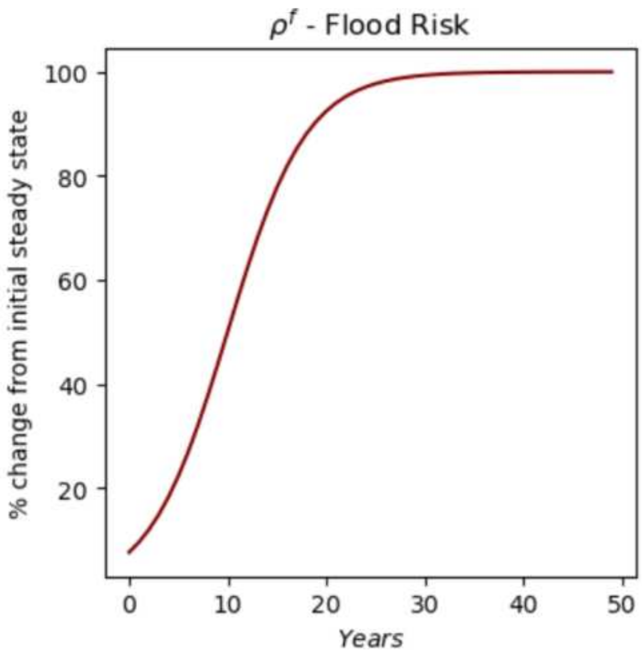
Variable	Aggregate value	Low income	High income	Description
C	0.98	0.33	1.63	Consumption
B	-0.05	-0.0997	-0.0082	Bonds
H	0.36	0.11	0.61	Housing
E	0.75	0.77	0.72	Elevation
I	0.46	0.36	0.56	Insurance

Variable	Value	Description
Damage	0.0005	Damage each period from flooding in housing units
Low income share of damage	15%	Share of damage absorbed by low income
MPC	0.066	Marginal propensity to consume, income weighted
Φ^H	0.0068	Housing adjustment costs
$\mathbf{1}(e \neq e')$	0.14	Proportion adjusting elevation

Notes: Initial steady state outcomes. Low income and high income values are the averages for above and below median income households.

Consistent with the data, only a fraction of households insure or elevate their homes; 46% and 75% respectively. The fraction insured is consistent with the proportion insured in the most high risk flood zones (Special Flood Hazard Areas). The proportion of homes elevated is higher than that in the data (on average the the sample used for my empirical results, 16% of homes are elevated); with the current model design, it appears hard to match the low degree of elevation. It could be that the current degree of home elevation seen in the data reflects housing stock built before the current level of flood risk, or when awareness of flood risk was lower. Alternatively, elevation could be unappealing to households, so a utility cost either on shifting from non-elevated to elevated housing or owning an elevated home could allow the model to better fit the data. For low income households, insurance take-up is lower and the proportion of elevated homes is higher, both consistent with the evidence shown in Figure 2a. Many households both take out insurance and elevate their homes, but few (only 2.1% of the total housing stock) leave themselves completely unprotected by having neither mitigation.

Figure 9: Flood risk increase



Notes: Rise in flood risk over the transition. At period 0, this rise in flood risk is announced to agents; figures in this section show the response to this shock.

I solve for a transition path when the probability of flood risk doubles, gradually over the course of 25 years. This is an increase in flood risk in line with an intermediate (RCP 4.5) climate change scenario; Ragno et al. (2018) finds that extreme precipitation events may become twice as frequent (in addition to more intense) in some densely populated urban areas, while IPCC (2021) find that globally, extreme precipitation would double the frequency of 1 in 50 year precipitation events, see Figure D.1 in the Appendix.[22] The path of increased risk is shown in Figure 9, and uses a logistic functional form, $\rho_t^f - \rho_0^f = 0.1 \times \frac{1}{1+\exp^{-(t-10)/4}}$.

Figure 10 shows the responses of insurance and elevation in the model. In response to a rise in flood risk, households increase insurance and elevation. Insurance take-up rapidly increases by up to 35%, while elevation increases more slowly and and ultimately rises by just over 6%. The relative size of these responses can be compared with the empirical responses in the previous section. By four years after the shock, in the data, insurance responds by

[22]Nationally in the US, the frequency of extreme precipitation is expected to to increase more gradually. Wing et al. (2022) find that under an RCP 4.5, intermediate scenario for emissions, climate change alone (discounting demographic changes) would increase the annual average exposure of the US population to flooding by 18.6%. However, because this increase is expected to be greater in already high-risk areas. See riskfinder.climatecentral.org for geographically detailed projections of future flood risk increases in the US; many high risk stations, such as Tampa Bay Florida, are expected to see much higher increases in the frequency of previously 1 in 100 year flood risks.

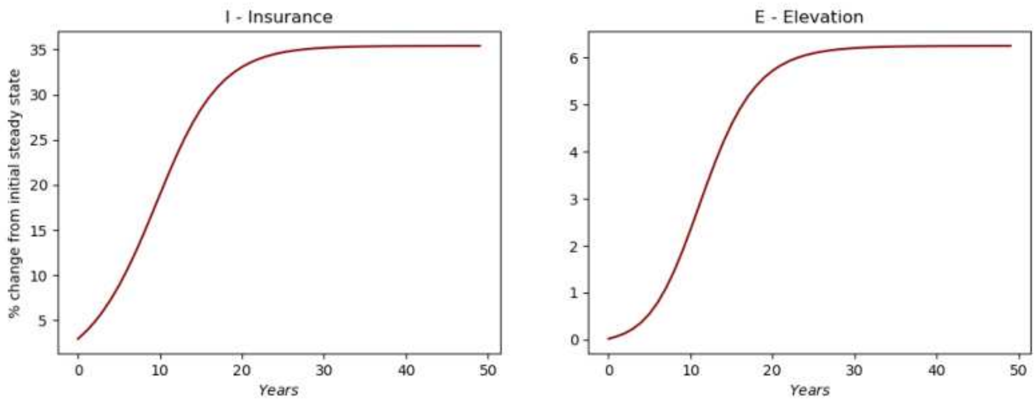
about 14 times more than elevation. In comparison, in the model, households are more reliant on elevation; the eventual relative response in the model of insurance is 6 times that of elevation. These sizes of relative responses are of a similar order of magnitude, but in the model households' elevation is more responsive to the shock. The reason for this greater reliance on elevation in the data could be the nature of the shock; a very persistent, but temporary rise in risk awareness in the data, compared to a permanent rise in risk in the model. If so, these differences could reflect an heightened willingness in the model to invest in elevation. However, given that overall steady state elevation rates are much higher in the model than in the data, this relatively higher responsiveness of elevation could instead reflect that there is some additional factor dis-incentivising elevation that is left out of the model, such as a dis-utility from elevation.

The model also reflects the heterogeneity in household responses. Low income households increasingly take out insurance; their insurance take-up rises by almost 50%, substantially more than that of high income households. Low income households do not increase their elevation rates. The relative response quantitatively is much more reliant on insurance than in the data, where elevation rates do rise, and insurance is 'only' 25 times more likely to be used than elevation as an approach to mitigating risk. In contrast, high income households rely on elevation much more to mitigate risk. The elevation of high income households rises by over 12% by the end of the transition. Insurance is taken up only twice as much as elevation, less than the 13 times seen in the data. Therefore, this evidence is matches the empirical evidence that high income households rely disproportionately on elevation to mitigate risk, whereas low income households rely more heavily on insurance.

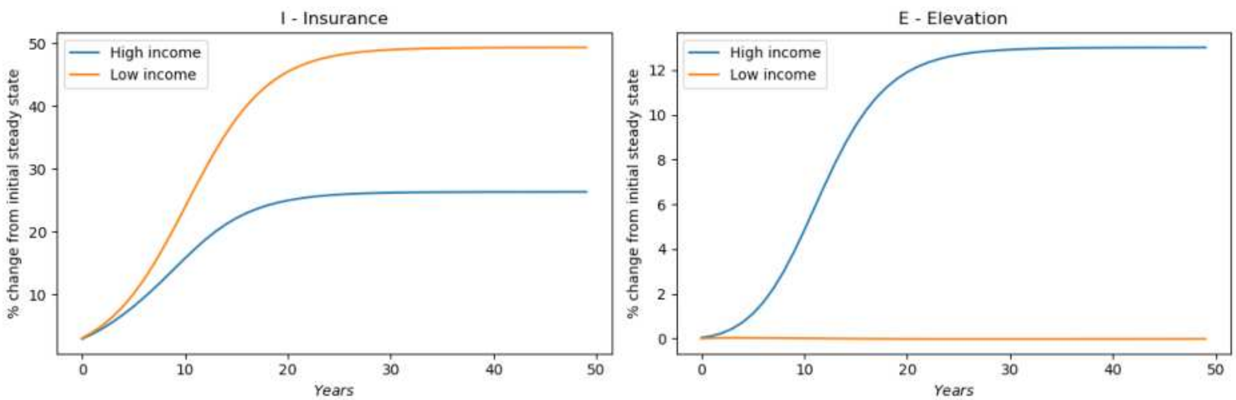
The model allows us to understand the impact of rising climate risk on aggregate outcomes (Figure 11) and inequality (Figure 12). As housing becomes more risky, households reduce their housing demand. In equilibrium, house prices fall as a result, immediately falling by 1.4% on announcement of the rising risk, and eventually falling by over 2%. During the transition, when flood risk is still rising, households' consumption remains relatively similar. Once the actual risk rises, and households begin to pay higher insurance premia and their housing stock loses value, consumption falls. Because housing and flood risk is only a small proportion of households' budget in the current calibration, this decline in consumption is small; only 1.4bp. In addition to the higher insurance and elevation rates, households also reduce their borrowing, giving more room for self-insurance via borrowing more if a flood shock occurred.

Figure 12 shows that these aggregate responses obscure substantial heterogeneity across households. Low income households take the opportunity of lower house prices to *increase*

Figure 10: Insurance and Elevation in model



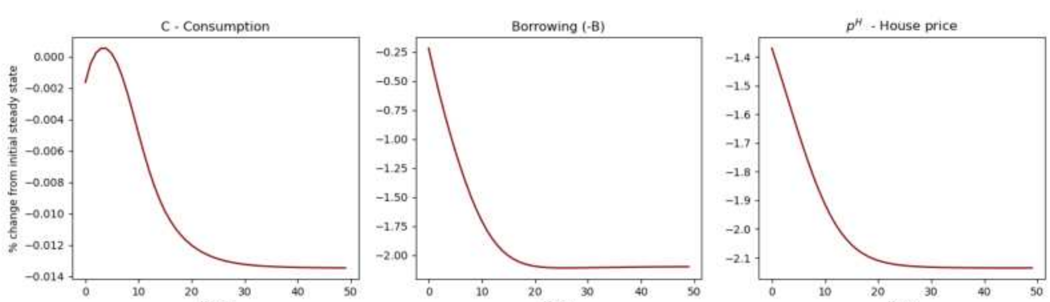
(a) Average



(b) Across incomes

Notes: Model transition path following an increase in flood risk shown in Figure 9. Panel 10a shows the average increase in the proportion of households with insured and elevated homes. Panel 10b shows the corresponding averages for portions of the income distribution.

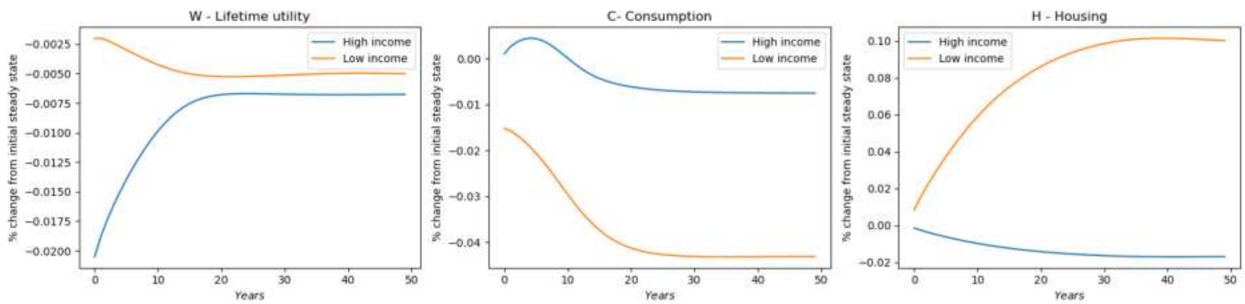
Figure 11: Aggregate responses to rising risk



Notes: Model transition path for aggregate variables following an increase in flood risk shown in Figure 9.

their housing stock, absorbing the fall in housing demand from the rich. The combination of higher housing demand and higher insurance premia paid on their housing result in a much larger fall in consumption of low income households. In contrast, high income households marginally increase consumption during the transition period, as they use the proceeds from selling their housing stock. The lifetime utility of agents has different dynamics; low income households are gradually more worse off as climate risk rises, while high income households suffer largest utility declines during the transition period, where they are selling off their previously high housing stock, which is now more risky.

Figure 12: Responses across the income distribution to rising risk



Notes: Model transition path following an increase in flood risk shown in Figure 9. Low and high income variables reflect averages of those below and above median within the income distribution.

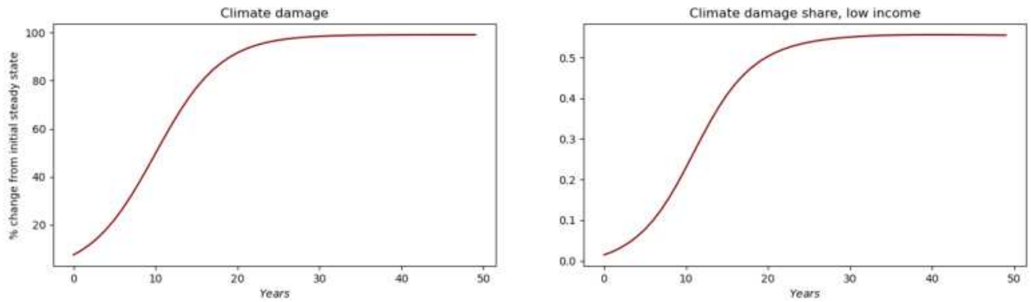
Finally, Figure 13 shows how these responses mitigate the damage to the economy from climate change. I define damage as the absolute amount of physical damage to housing:

$$\text{Damage} = H^{NE}\rho^f\tau^f + H^E\rho^f\tau^f(1-\tau^e)$$

Where H^{NE} and H^E are the total amounts of non-elevated and elevated housing, respectively. These are multiplied by the per-period expected amount of damage given flood probability ρ^f and damage of floods, τ^f, and accounting for the fact that the elevated homes experience $1-\tau^E$ less damage. This sets aside insurance, because households also have to pay for insured climate damage via insurance premia (albeit, subject to a subsidy).

Absent any change in behaviour from households, damage would rise by 100%. Figure 13 shows that the household responses to climate risk by increasingly elevating homes only marginally reduces the rise in risk. Although an increasing proportion of households have more elevated homes, this is disproportionately households with very little housing wealth. The aggregate increase in houses that are elevated is much smaller (see Figure D.4a in the Appendix). An alternative calibration of the economy might make this adaptive channel more powerful in mitigating damages. The transition path is also regressive, with climate

Figure 13: Climate damage in response to rising risk



Notes: Model transition path following an increase in flood risk shown in Figure 9. Low and high income variables reflect averages of those below and above median within the income distribution.

damage weighing more heavily on low income households. As these households do not increase the elevation, and overall increase their housing stock, they bear a larger proportion of the climate damage while flood risk rises. This increase is, however fairly small in magnitude under the current calibration, only changing by 50bp.

4 Conclusion

As climate change worsens, increasing damage from extreme weather events is expected. This paper explores how increasing extreme weather events will affect economic outcomes, given household responses. Using empirical evidence from administrative US flood data and a proxy for awareness of flood risk, I find that household responses are highly heterogeneous. All households respond to rising flood risk by insuring more; richer households respond marginally more. However, there is considerably heterogeneity in adaptive investments; high income households are much more likely to make adaptive investments.

One natural interpretation of this heterogeneity is that financial constraints may limit low income households' desire to make adaptive investments. As rising risk will play out over many years, financially constrained and low income households may be less inclined to invest upfront in adaptive investments which may only pay off well in the future. As low income households delay investments, then as these risks rise, damage may fall more heavily on low income households.

I develop a heterogeneous agent model which explicitly models households' decisions to insure or elevate their homes. Consistent with the empirical evidence, high income households rely more on adaptive investments to insulate themselves from climate risk. The model allows a broader understanding of aggregate outcomes that result from the insurance and elevation decisions. In addition to not adapting their homes, low income households buy more of the housing stock from richer households, as house prices fall. This means they are doubly exposed to rising climate risk. As a result, the incidence of rising climate risk is regressive; low income households shoulder an increasing burden as climate change worsens.

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Appendix

A NFIP and Home Elevation

This section gives further contextual details on what home elevation is and what it results in for insurance premia. Figure A.1 shows an example NFIP rate table, where elevation reduces the premia charged for property insurance. Figure A.2 shows examples of elevated homes, and how this defends a home from flooding. Figure A.3 shows one methods of elevating a home, and a home in the process of being elevated. Figure A.4 shows historic examples of elevated and non-elevated homes in New Orleans in 1927, along with an advertisement for home raising services from 1901.

Figure A.1: Example NFIP rate table (2021)

RATE TABLE 3B. REGULAR PROGRAM – POST-FIRM CONSTRUCTION RATES[1,2]

ANNUAL RATES PER $100 OF COVERAGE (Basic/Additional)

FIRM ZONES AE, A1–A30 — BUILDING RATES

ELEVATION OF LOWEST FLOOR ABOVE OR BELOW THE BFE[3,4]	1 FLOOR No Basement/Enclosure/ Crawlspace[5,6]		MORE THAN 1 FLOOR No Basement/Enclosure/ Crawlspace[5,6]		MORE THAN 1 FLOOR With Basement/Enclosure/ Crawlspace[5,6]		MANUFA (MOBILE)
	1-4 Family	Other Residential, Non-Residential Business, Other Non-Residential[9]	1-4 Family	Other Residential, Non-Residential Business, Other Non-Residential[9]	1-4 Family	Other Residential, Non-Residential Business, Other Non-Residential[9]	Single Family
+4	.31 / .09	.28 / .13	.27 / .08	.22 / .08	.24 / .08	.20 / .08	.32 / .16
+3	.35 / .09	.32 / .15	.31 / .08	.25 / .08	.27 / .08	.23 / .09	.37 / .18
+2	.51 / .11	.46 / .20	.44 / .08	.36 / .08	.32 / .08	.28 / .10	.54 / .24
+1	.96 / .17	.84 / .31	.80 / .08	.66 / .09	.46 / .08	.36 / .12	1.02 / .40
0	2.25 / .27	1.92 / .50	1.79 / .08	1.44 / .14	.68 / .08	.58 / .14	2.39 / .71
−1	5.47 / .36	4.58 / .69	4.40 / .08	3.54 / .15	1.17 / .08	.86 / .17	5.83 / 1.13
−2[8]	8.07 / .70	6.88 / 1.35	6.53 / .13	5.25 / .26	***	***	8.61 / 2.19
−3[8]	10.00 / 1.20	8.76 / 2.30	8.32 / .22	6.77 / .47	***	***	10.59 / 3.41
−4[8]	12.06 / 1.80	10.76 / 3.45	10.26 / .36	8.46 / .77	***	***	12.68 / 4.77
−5[8]	13.61 / 2.41	12.34 / 4.60	11.79 / .57	9.88 / 1.16	***	***	14.21 / 6.00
−6[8]	13.96 / 2.96	12.86 / 5.63	12.36 / .84	10.56 / 1.69	***	***	14.51 / 6.84
−7[8]	14.20 / 3.49	13.34 / 6.53	12.87 / 1.11	11.15 / 2.21	***	***	14.85 / 7.50
−8[8]	14.26 / 3.99	13.44 / 7.46	13.23 / 1.40	11.59 / 2.75	***	***	14.89 / 8.04

Figure A.2: Examples of home elevation

(a) Holycross, New Orleans (2014)

(b) Tangier Island, Virgina

Figure A.3: Insurance, elevation, and flood risk across the income distribution

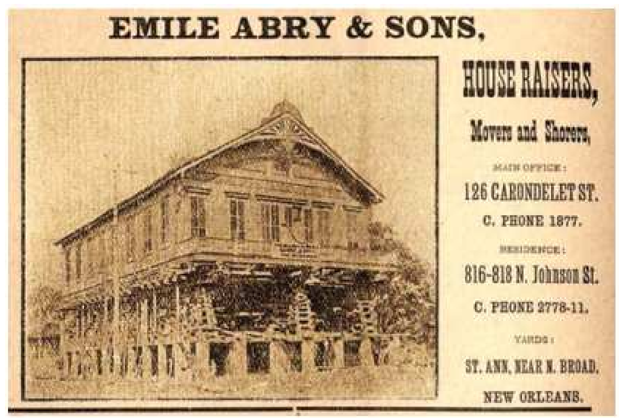
(a) Home elevation process

(b) Example recently elevated home

Notes: Diagram of how to elevate a home, from Louisiana State University (2005), and example of a recently elevated home.

Figure A.4: Historic elevation examples

(a) New Orleans during the Great Mississippi Flood (1927)



(b) Advert for building elevation services (1901, New Orleans)

Notes: Imagine of elevated and non-elevated homes in New Orleans, following the Great Mississippi Flood (1927), and advertisement for building raising services.

B Relocation

This sections presents further results showing how the rate of relocation interacts with the main results of the paper. Firstly, Table B.1 shows a comparison of key economic outcomes in areas with high and low relocation rates, used in section 2.5. This shows that for most economic outcomes, high and low relocation areas are similar; high relocation areas have marginally higher incomes, higher house prices, are marginally younger and less educated. The major difference between the two (other than relocation rates) is the share of the population in rural areas. Low relocation rate areas are much more likely to be rural; intuitively, there may be fewer very similar homes in less dense areas.

Figure B.1 shows the difference in insurance take-up, split by the relocation rate and income of areas. Similarly to the main results, high income areas tend to take up more insurance following a shock in both types of areas. Insurance take-up is slightly higher also in high relocation areas. This is consistent with the results in Figure 8 that suggest that households in high relocation areas are less reliant on elevation to accommodate risk, so they compensate for this by increasing insurance take-up.

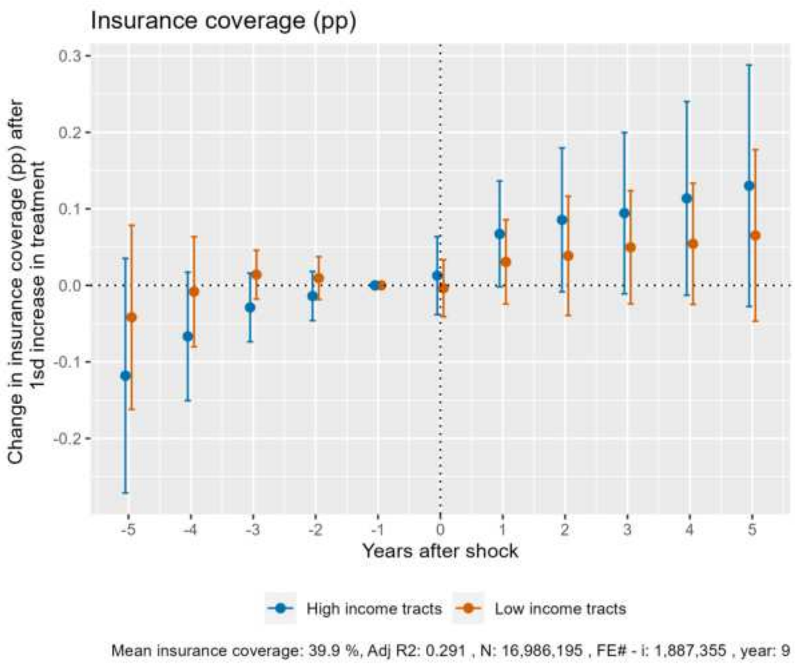
Figure B.2 shows the response of home elevation split by relocation levels, using different measures for relocation to Figure 7. Here, rather than the total number of movers (including movers within county) this shows a measure of relocation based on net migration and outward migration from county. Similar to the main measure, this is as a share of total population, and the counties are split by whether they have an above or below median rate of relocation. The results are similar to the main results' areas with low relocation levels tending to see more response of home elevation following a shock.

Table B.1: Comparison of observables - low and high relocation areas

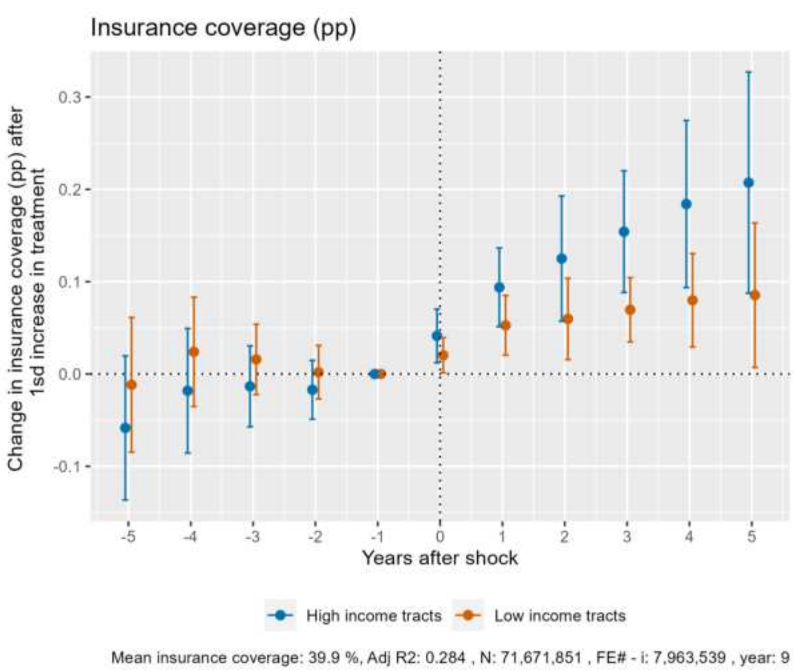
	Low relocation	High relocation
Relocation share	0.11	0.18
Net migration share	-0.01	0.01
Median household income	43,532.96	45,005.21
Median age	41.67	38.04
Unemployment rate	7.14	7.63
Labour force participation	0.75	0.73
Share of population with high school or less education	0.38	0.33
Share of population in poverty	0.14	0.14
Share of population in rural areas	0.73	0.46
Share of population in owner-occupied housing	0.75	0.67
Median value, mortgaged houses	131,459.60	151,038.30

Notes: Counties split by relocation share (above and below median), as described in text. Other variables are from the 5y 2010 ACS and 2010 census.

Figure B.1: Insurance response - comparison of low and high migration areas, split by income group

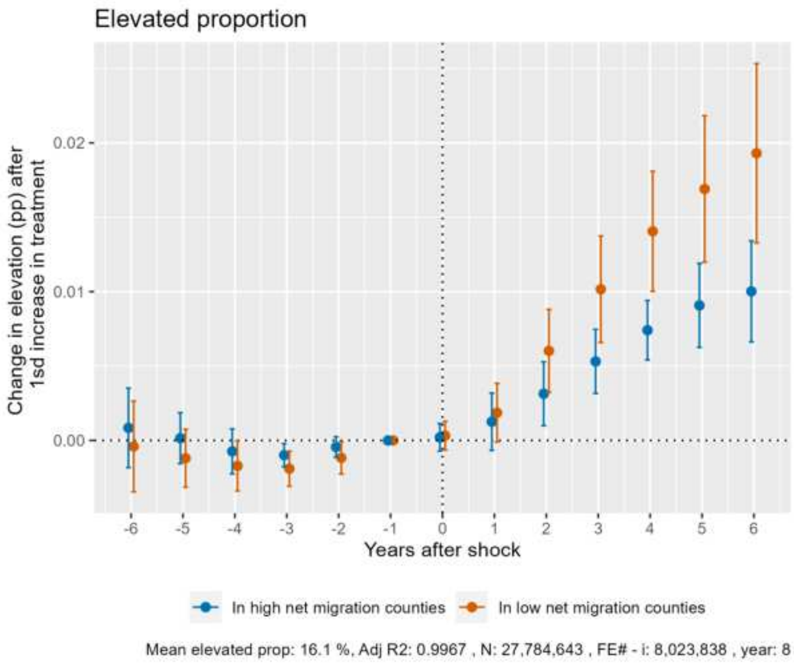


(a) Low relocation areas

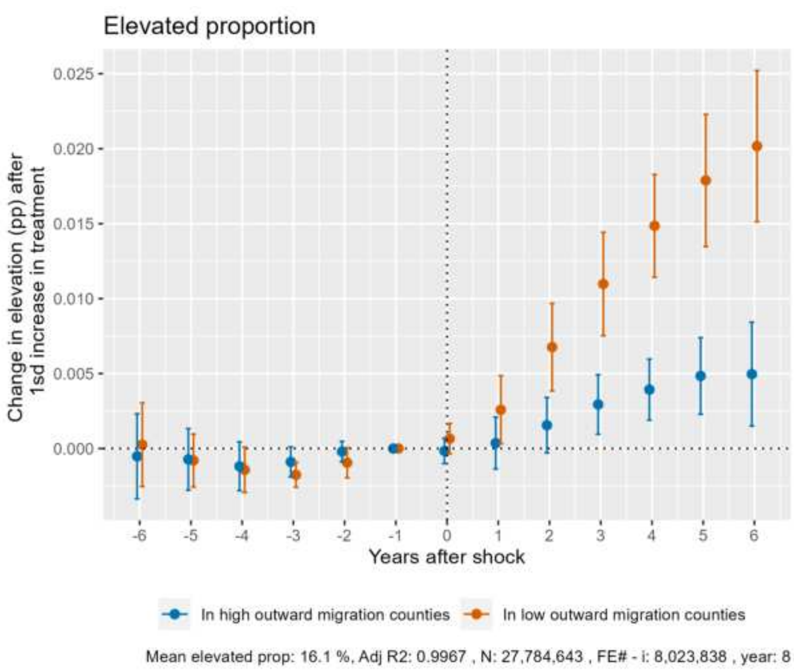


(b) High relocation areas

Figure B.2: Elevation response by relocation levels - alternative relocation measures



(a) Relocation measure: net migration from county



(b) Relocation measure: outward migration from county

Table B.2: Summary statistics

By census tract	
No. policies	64
No. housing units	1864
Perc. insured of all housing units	3.2%
Perc. elevated of insured	16.1%
Overall	
Av. policy cost (2015$)	$754

C Further results and robustness

This section lists a number of further empirical results, described in Section 2.5. The first set of results show alternative flood awareness proxies. Figures C.1 and C.2 show results using a flood awareness proxy using the count of extreme rainfall days, rather than average precipitation. Figures C.3 and C.4 use a flood awareness proxy using the county of flood insurance claims, rather than precipitation. Figures C.5 and C.6 show results where the flood awareness proxy is constructed using the full friendship network, rather than only faraway friends. Figures C.7 and C.8 using *local* tract rainfall, rather than rainfall in the friendship network. See the Section 2.5 for detailed discussion.

Next, Figures C.9 and C.10 show results where the regressions are run at the aggregated, census tract level, by taking the average elevation and insurance results within a tract and using census tract fixed effects. The results are qualitatively similar; insurance and elevation proportions rise, at a somewhat more attenuated level, with high income households' proportion rising more. These results have the downside of not being able to focus on individual responses, which means that for elevation proportions, there may be selection of different types of homes into the insurance dataset (rather than particular properties changing elevation). This may be the reason why the elevation responses are somewhat smaller and less heterogeneous here, if individual households who have elevated homes are more likely to purchase insurance following the shocks.

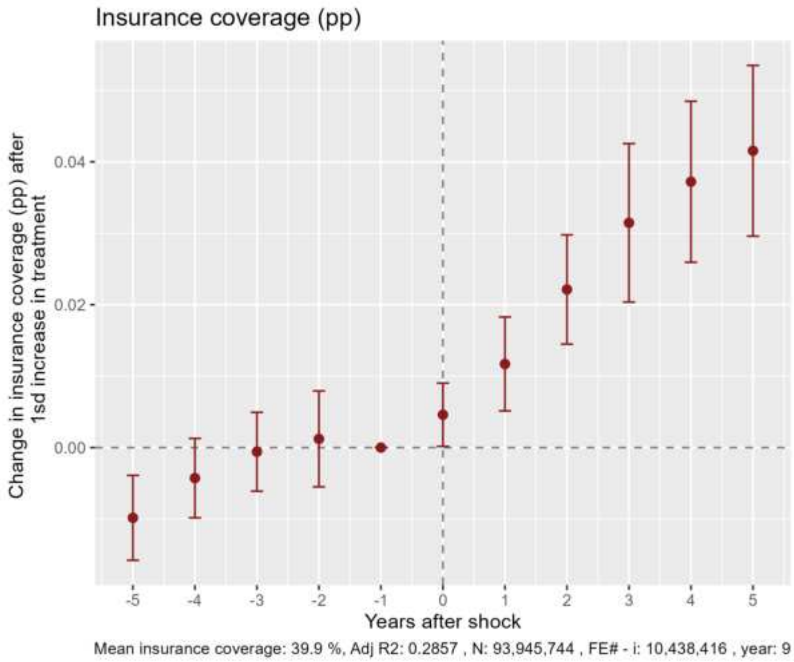
Finally, I investigate the responses to changes in the cost of insurance policies, which could be used to further discipline the calibration of the model in future. To estimate these, I first generate an unexplained component of the policy cost, by regressing the insurance policy cost against a range of explanatory variables, including property characteristics, flood risk and when the insurance was taken out.[23] The residual of this regression would primarily describe the change in pricing of risk over time - for instance, in the aftermath of legislation in 2014 to increase premia of higher risk properties, and the more recent Risk Rating 2.0 reforms. The aim with this residualisation is that changes in insurance pricing do not represent changes

[23] I regress the log of the policy cost reported in the NFIP dataset, for single family homes, on a set of explanatory variables. The full list of explanatory variables used is the log of a set of continuous variables: the total contents insurance coverage, building insurance coverage, building replacement cost increased cost of compliance premium, federal policy fee. In addition to these continuous variables, I use dummy variables for a set of categories: the level of the base flood elevation, the community rating system class code, building and contents deductible level, the flood zone (rated and current, where different), the NFIAA surcharge, lowest flood elevation, number of floors, the year and month the policy came into effect, whether the property was build after flood mapping, whether the building was floodprooed and whether the rate used is grandfathered. Because of the size of the dataset, I generate residuals from running these regressions on seperate portions of the data, 100 in total. The R^2 of the regressions are typically around 0.75 (and very similar across regressions), and with similar coefficients.

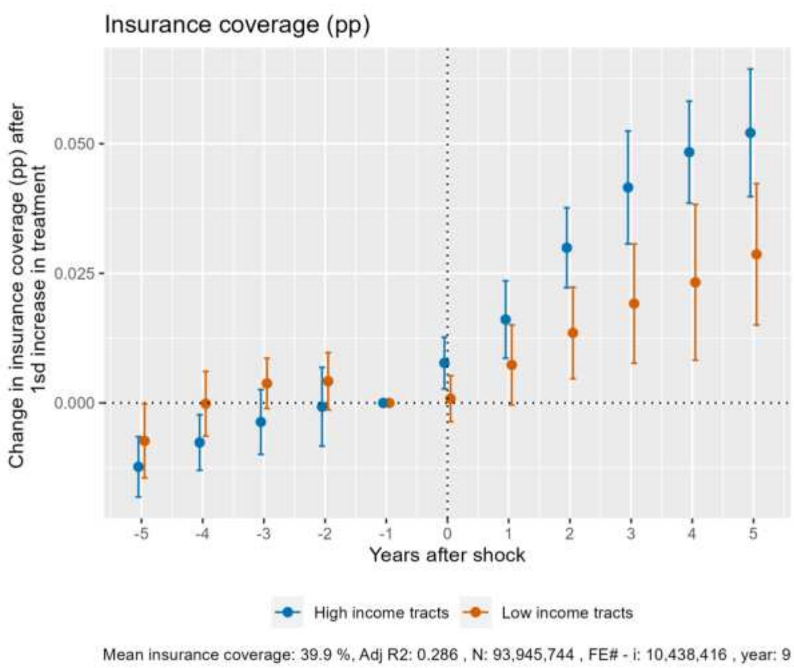
in underlying risk, but otherwise exogenous changes in the pricing of risk. For the elevation results, the residual for the specific property is used. For insurance, as there are no observables for the uninsured properties, I use a tract-level average residual, assuming that the pool of properties in the sample (which are all insured at some point in time) is relatively well reflected by those which are insured.

Figures C.11 and C.12 show the results of the main specifications 2 and 3, using the residuals of these regressions as the shock variable. Insurance take-up falls when policy costs rise, by 0.2pp when policy costs rise by 1%. The fall is greater for low income areas. In the aftermath of the shock, as expected, the effect lessens. This is heterogeneous; eventually high income households increase insurance uptake, perhaps reflecting that increases in insurance costs are interpreted as higher risk, and eventually more insurance is taken up. In lower income areas, insurance take-up is persistently lower, perhaps reflecting persistence of habits in taking up (or failing to take up) insurance. Elevation increases in the aftermath of the shock, perhaps reflecting the relative increase in cost of insurance relative to elevation to mitigate risk. As in the main results, this change is almost entirely driven by higher income areas. However, all these elevation results show some signs of pre-trends, perhaps indicating that risk-dependent, time-varying insurance pricing is anticipated by households when making the longer-term elevation decisions.

Figure C.1: Insurance response - alternative shock, using extreme precipitation



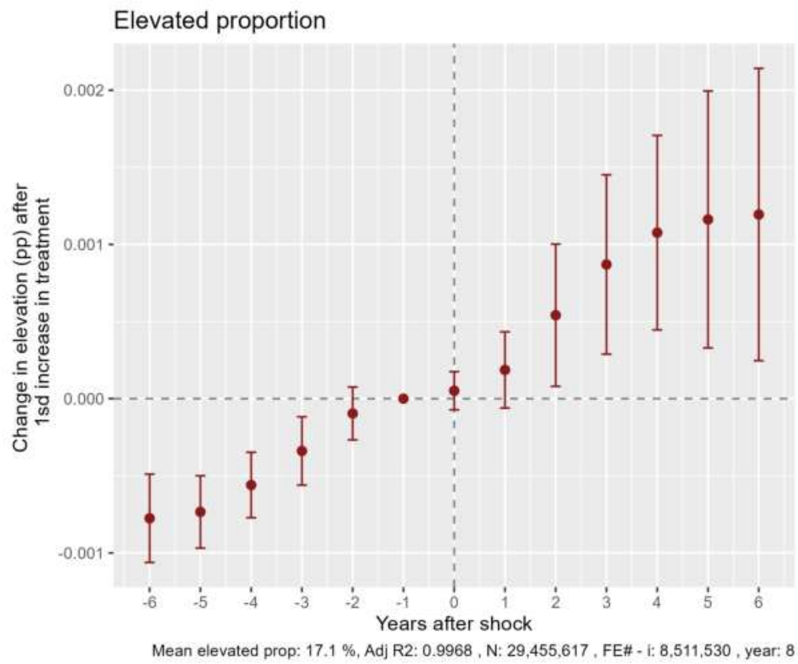
(a) Overall insurance response



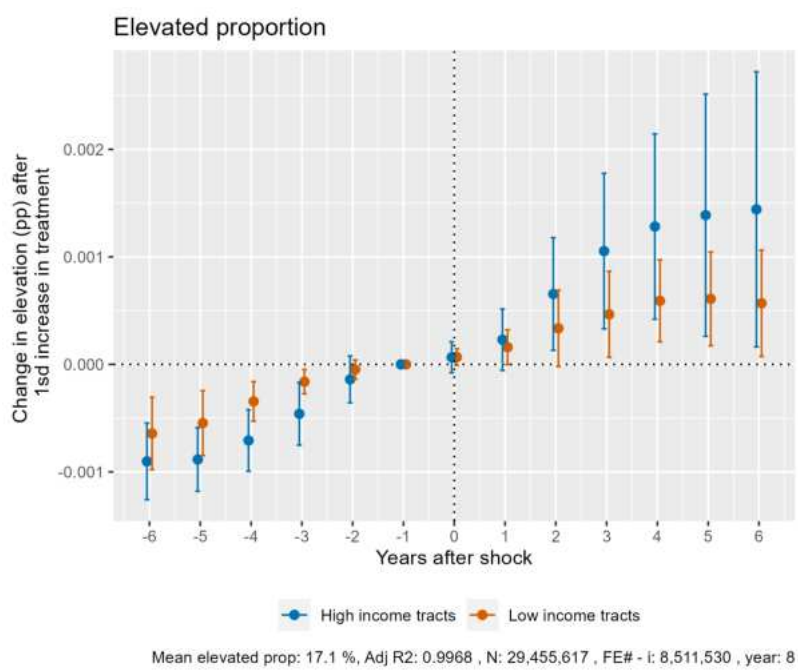
(b) By income group

Notes: Response of insurance take-up to the flood awareness proxy, using specifications 2 and 3. This flood awareness proxy uses a measure of extreme (3 inches per day) precipitation, rather than average precipitation.

Figure C.2: Elevation response - alternative shock, using extreme precipitation



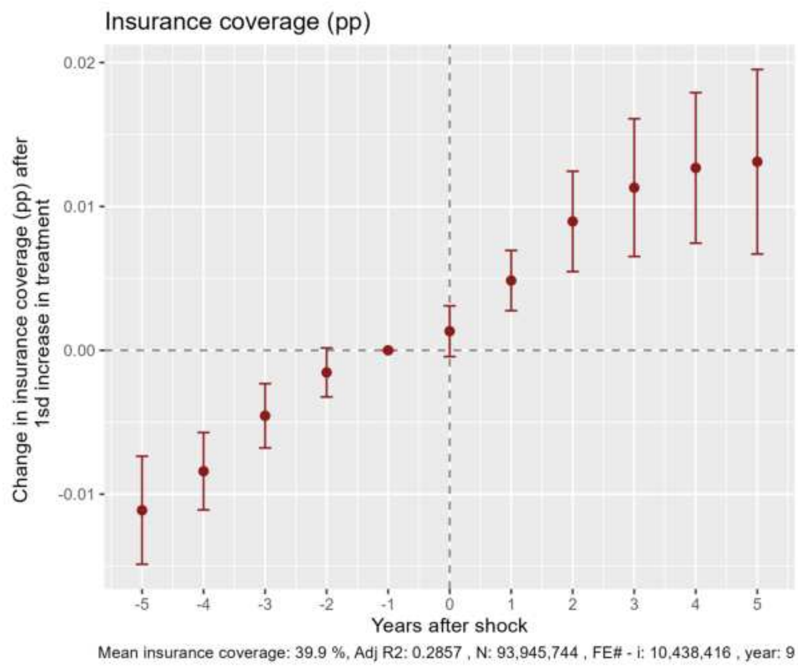
(a) Overall elevation response



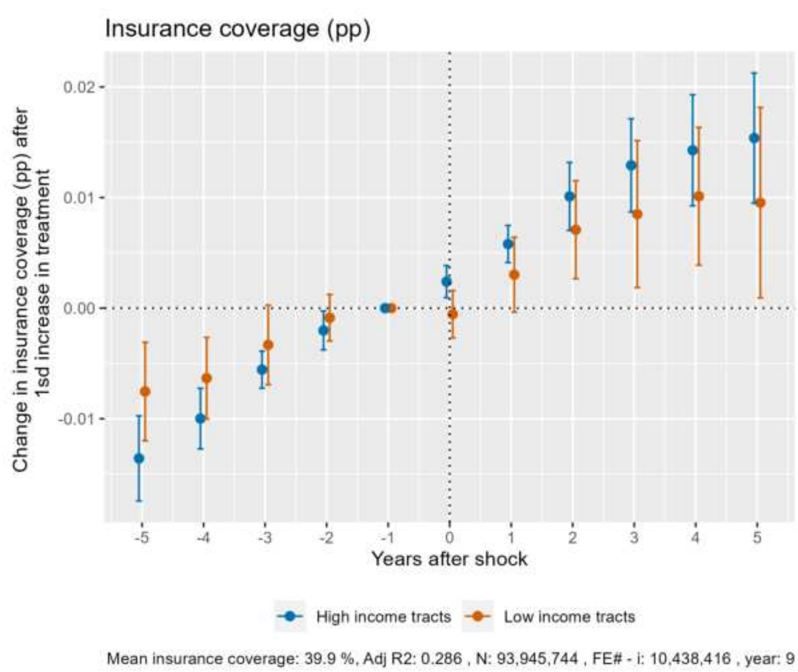
(b) By income group

Notes: Response of home elevation to the flood awareness proxy, using specifications 2 and 3. This flood awareness proxy uses a measure of extreme (3 inches per day) precipitation, rather than average precipitation.

Figure C.3: Insurance response - alternative shock, using number of flood claims



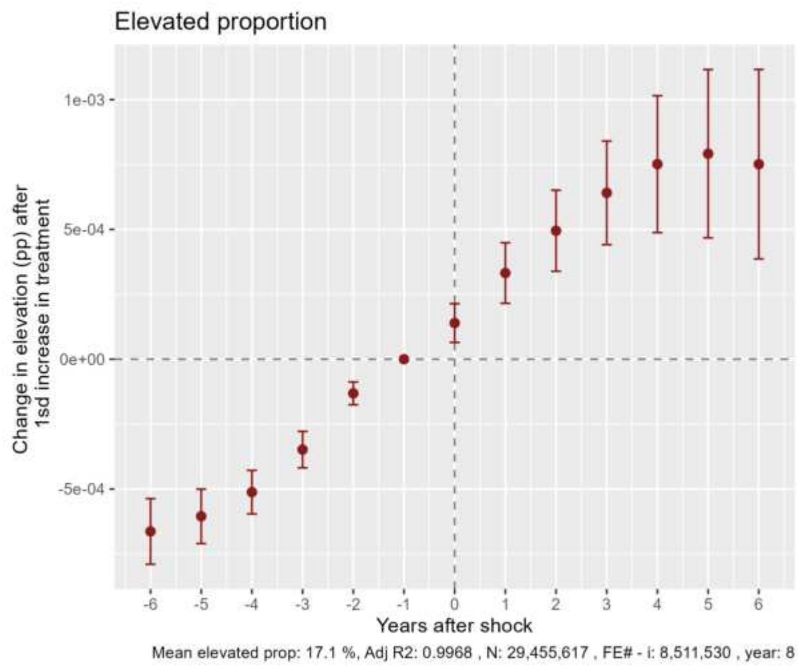
(a) Overall insurance response



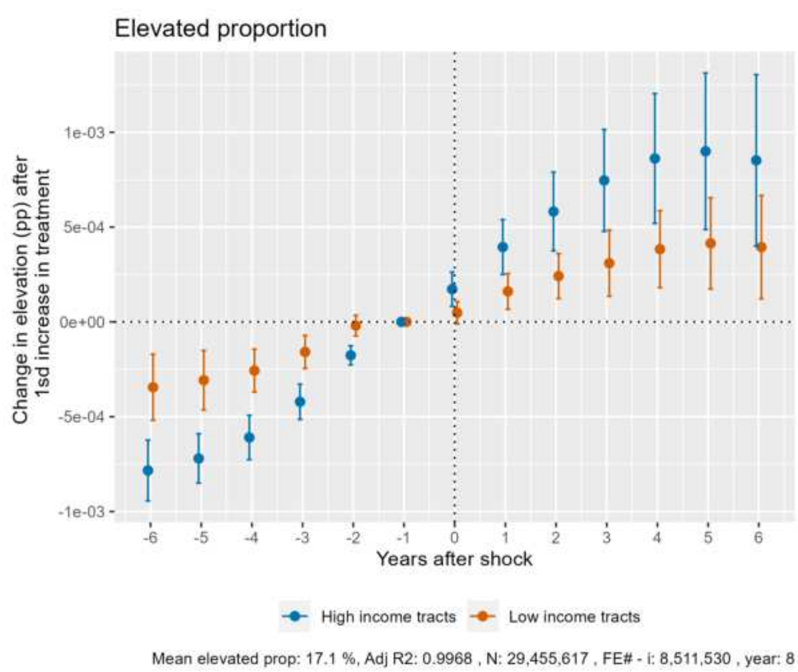
(b) By income group

Notes: Response of insurance take-up to the flood awareness proxy, using specifications 2 and 3. This shows the responses using an alternative flood awareness proxy, using the count of flood claims made in the distanced friends' census tracts (rather than precipitation).

Figure C.4: Elevation response - alternative shock, using number of flood claims



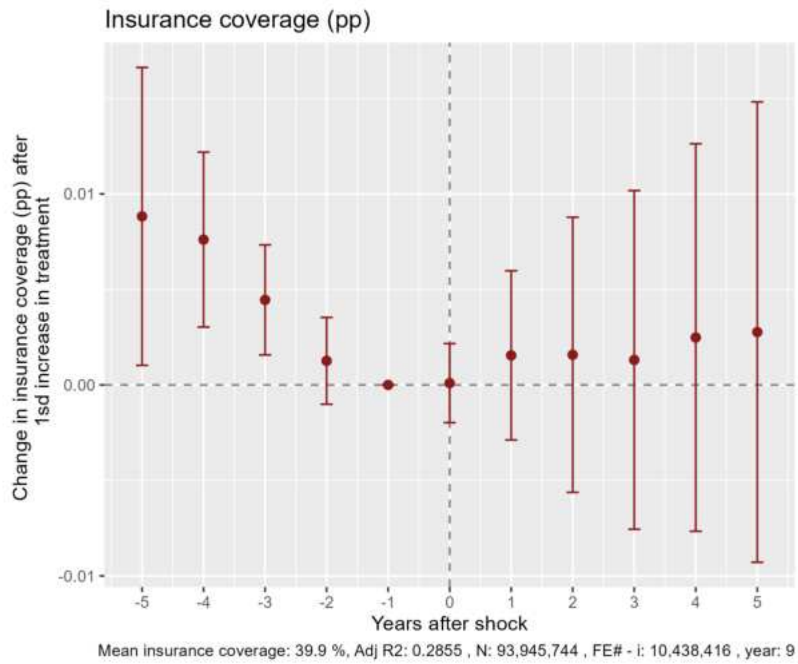
(a) Overall elevation response



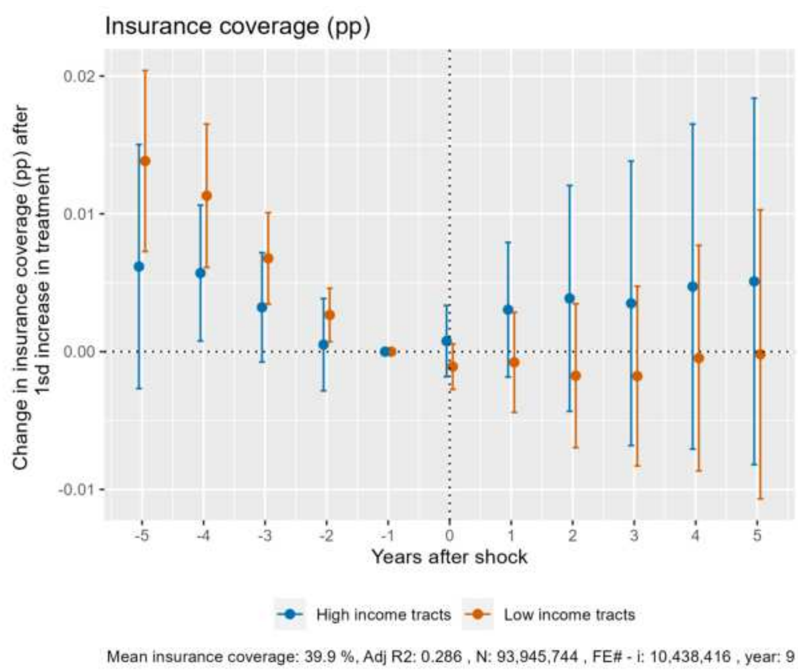
(b) By income group

Notes: Response of home elevation to the flood awareness proxy, using specifications 2 and 3. This shows the responses using an alternative flood awareness proxy, using the count of flood claims made in the distanced friends' census tracts (rather than precipitation).

Figure C.5: Insurance response - alternative shock, including full friendship network



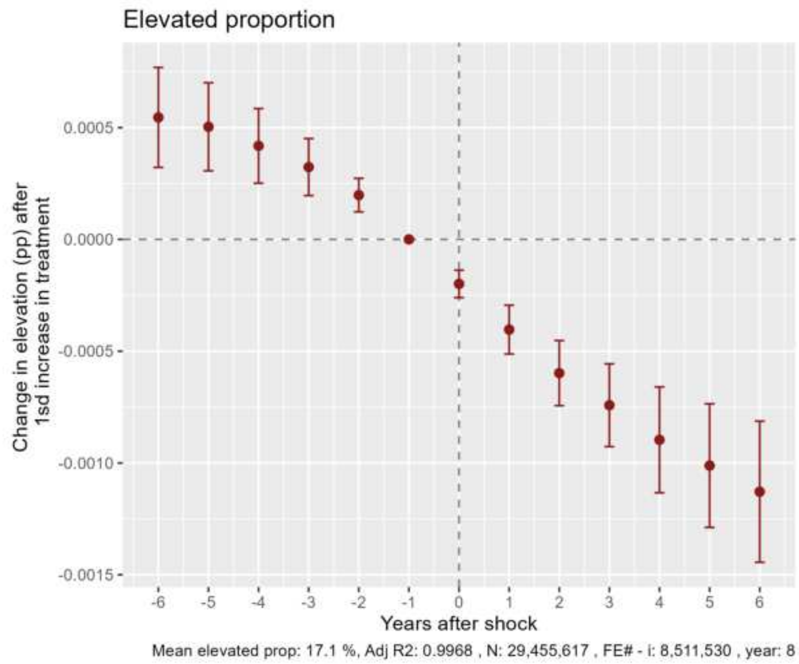
(a) Overall insurance response



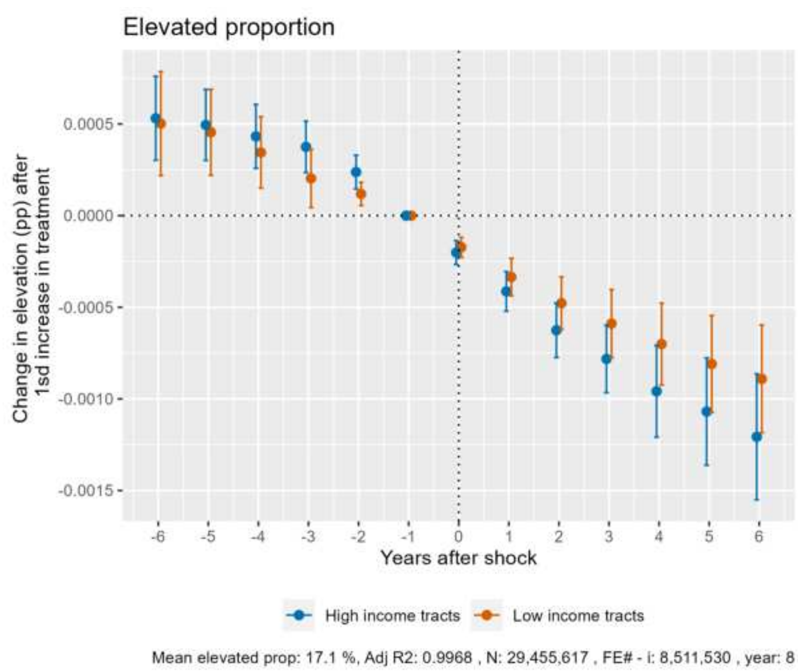
(b) By income group

Notes: Response of insurance take-up to the flood awareness proxy, using specifications 2 and 3. This shows the responses using an alternative flood awareness proxy, constructed using the full friendship network (rather than only far-away friends).

Figure C.6: Elevation response - alternative shock, including full friendship network



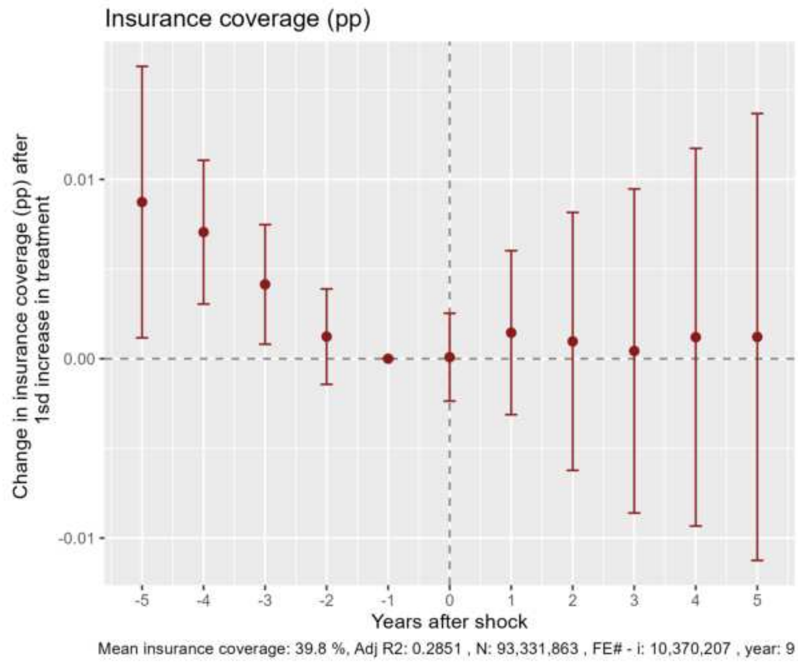
(a) Overall elevation response



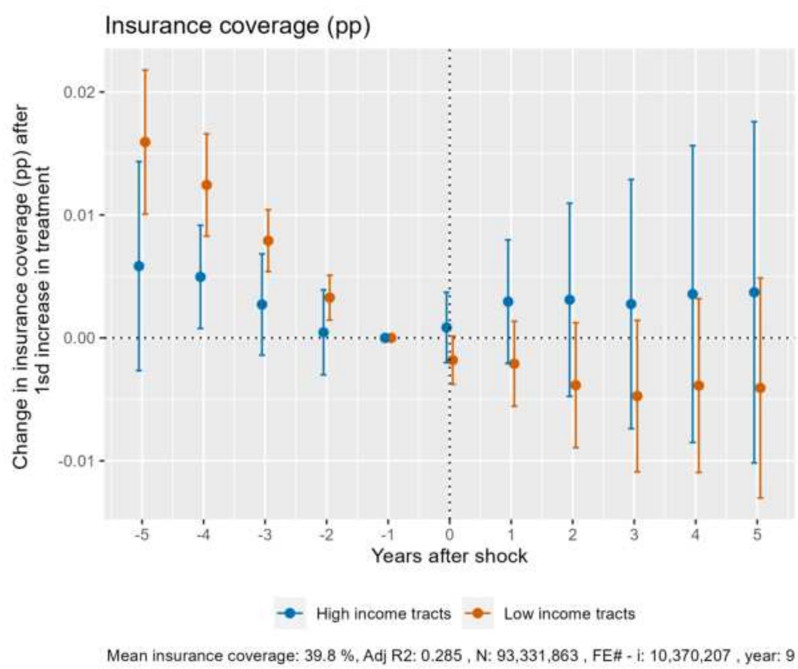
(b) By income group

Notes: Response of home elevation to the flood awareness proxy, using specifications 2 and 3. This shows the responses using an alternative flood awareness proxy, constructed using the full friendship network (rather than only far-away friends).

Figure C.7: Insurance response - response to local rainfall



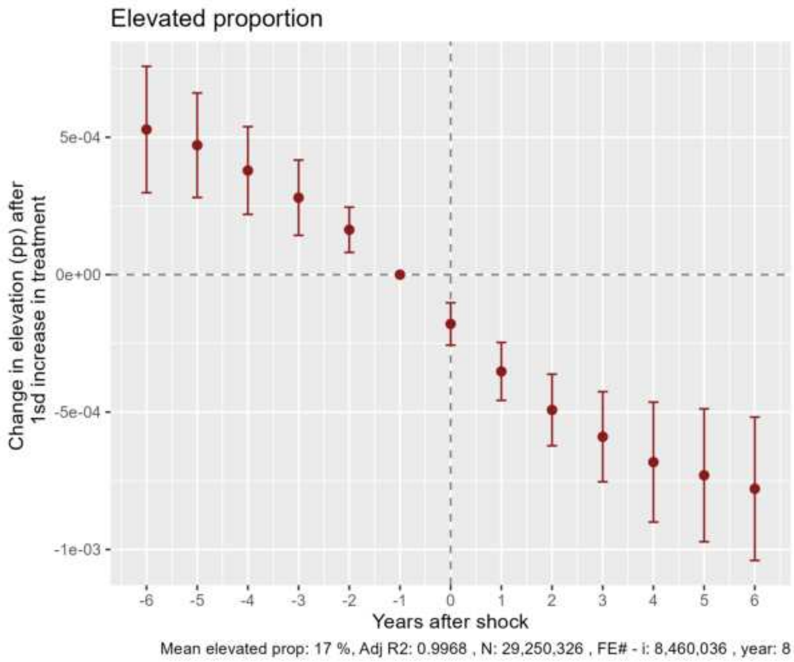
(a) Overall insurance response



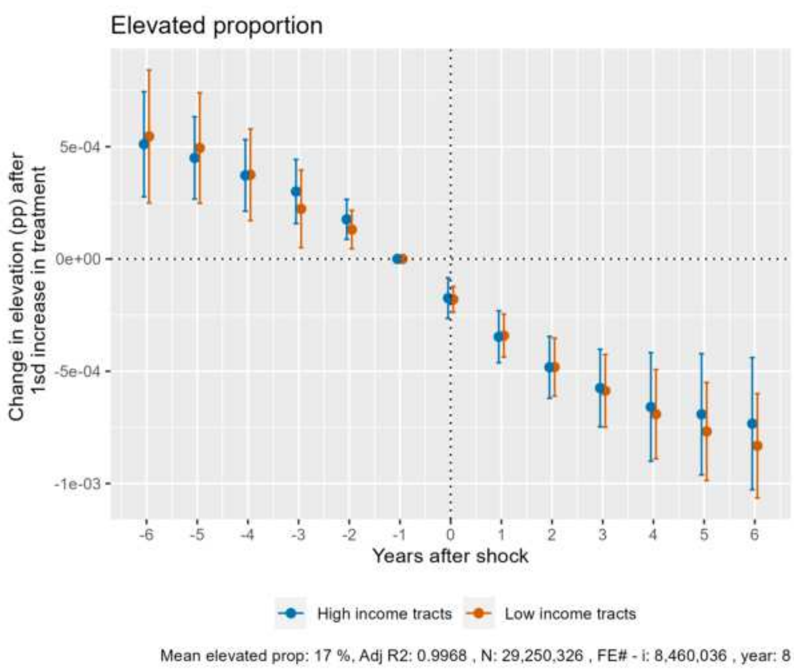
(b) By income group

Notes: Response of insurance take-up to local rainfall, using specifications 2 and 3. Local rainfall is tract average precipitation, using PRISM data described in the text.

Figure C.8: Elevation response - response to local rainfall



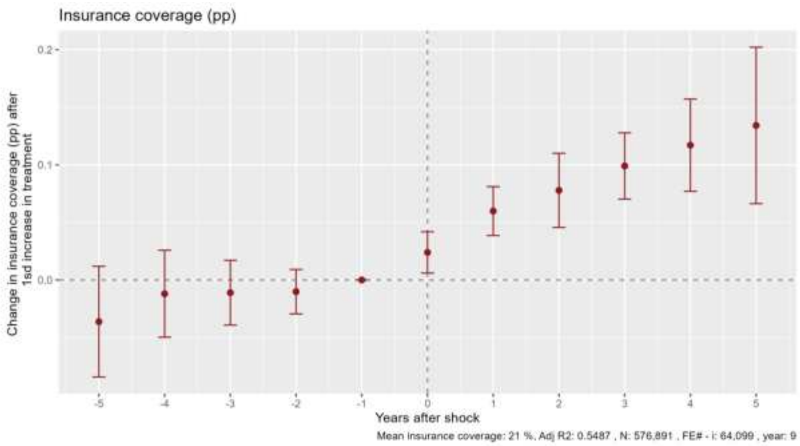
(a) Overall elevation response



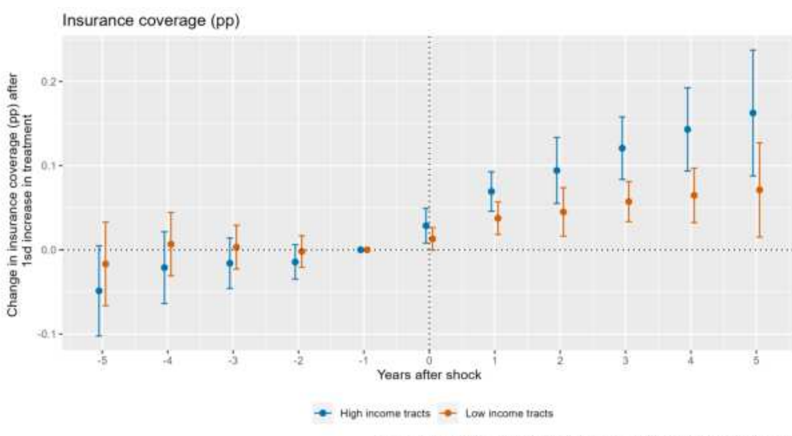
(b) By income group

Notes: Response of home elevation to local rainfall, using specifications 2 and 3. Local rainfall is tract average precipitation, using PRISM data described in the text.

Figure C.9: Insurance response - tract-level aggregated specification



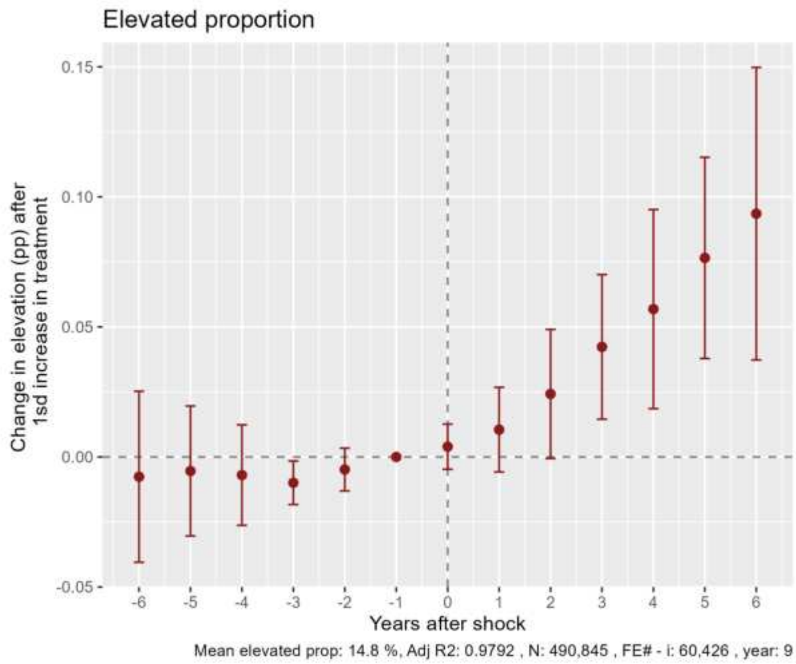
(a) Overall insurance response



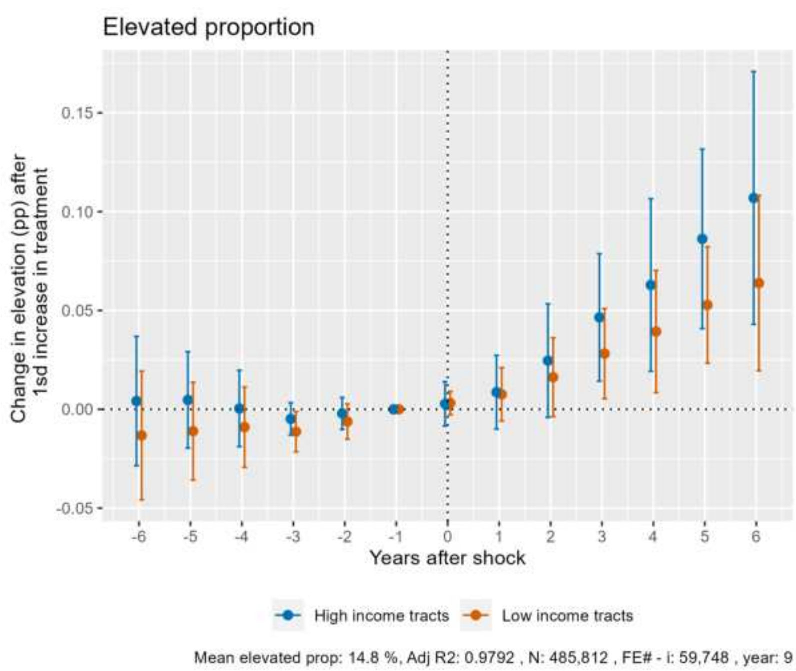
(b) By income group

Notes: Response of insurance take-up to the flood awareness proxy, using specifications 2 and 3. These versions are aggregated to the census tract level, using census tract fixed effects and average insurance proportions within the tract

Figure C.10: Elevation response - tract-level aggregated specification



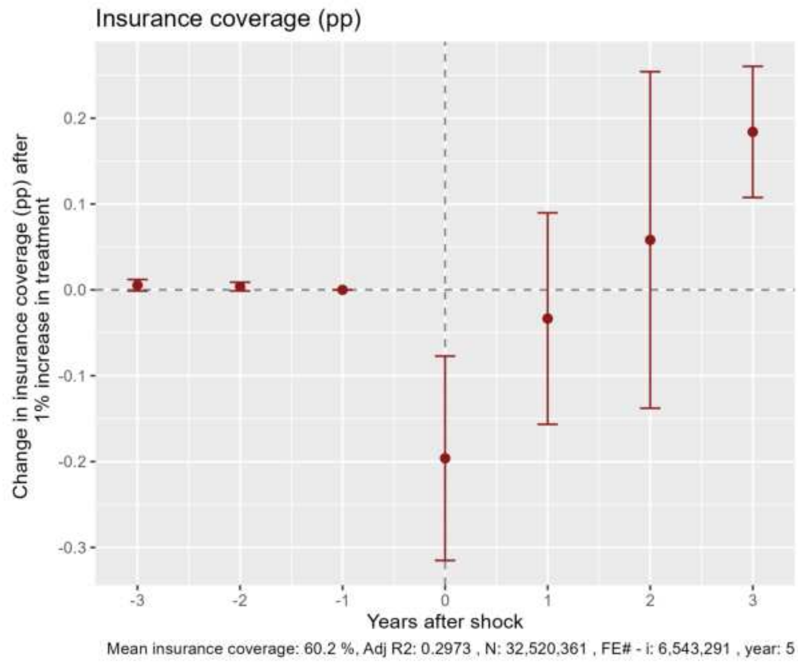
(a) Overall elevation response



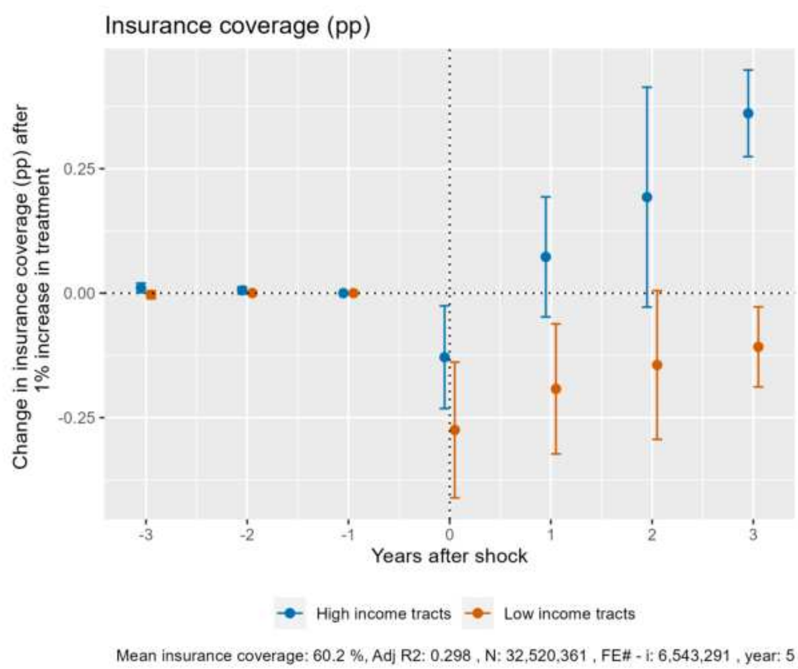
(b) By income group

Notes: Response of home elevation to the flood awareness proxy, using specifications 2 and 3. These versions are aggregated to the census tract level, using census tract fixed effects and average elevation proportions within the tract

Figure C.11: Insurance response - increases in insurance policy cost



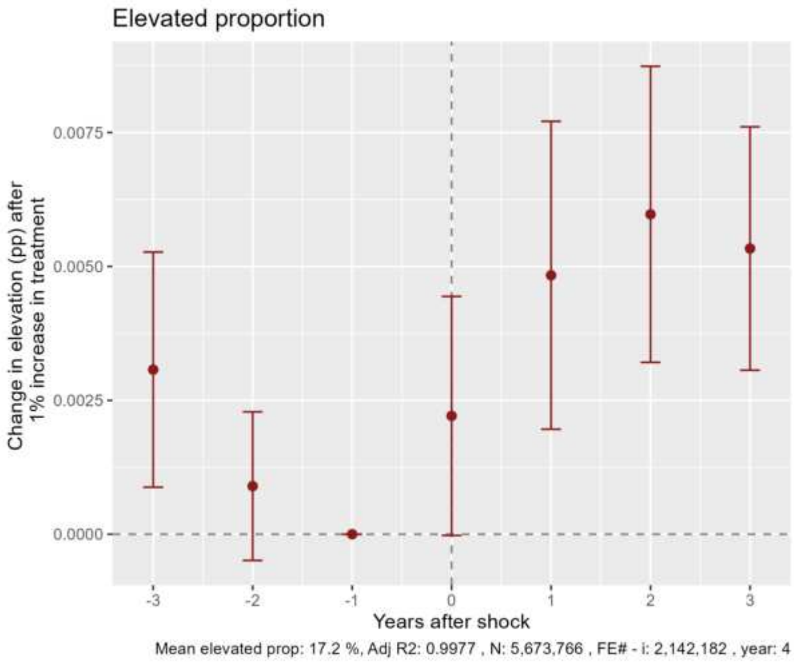
(a) Overall insurance response



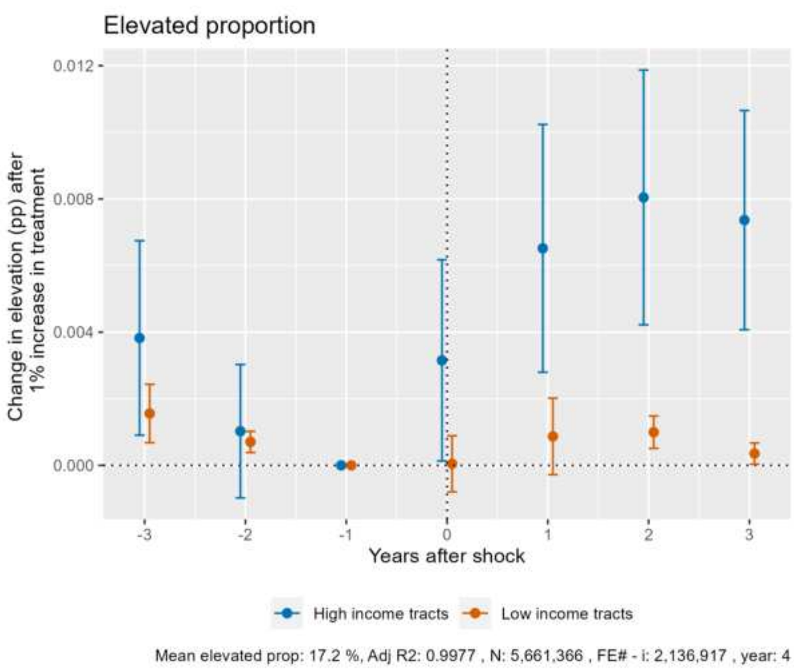
(b) By income group

Notes: Response of insurance take-up to a change in tract-level typical insurance pricing, using specifications 2 and 3. The insurance price is residualised against a range of explanatory variables, as described in text.

Figure C.12: Elevation response - increases in insurance policy cost



(a) Overall elevation response



(b) By income group

Notes: Response of insurance take-up to a change in property-level insurance pricing, using specifications 2 and 3. The insurance price is residualised against a range of explanatory variables, as described in text.

D Model

D.1 Model description

Full household problem Key additions to standard two-asset model:

- h: Illiquid asset is housing, and gives utility to agents
- f: flood state, $\{0,1\}$, τ^f: Damage proportion if flooded, ρ^f: probability of flood.
- e: binary elevation choice $\{0,1\}$, at elevated houses have a premium p^e and reduce loss if flooded by τ^e
- i: binary insurance $\{0,1\}$, chosen before exogenous states are realised. Full insurance only, which which is priced based on a potential subsidy (or premium) q compared to actuarially fair value $\rho^f\tau^f(1-\tau^e e)(p^h+p^e e)$ per unit of housing.

$$V(b,h,i,e;s,f) = \max_{b',h',i',e'} \{u(c) + \gamma u(H(h,f,i,e)) + \beta\,\mathbb{E}[V(b',h',i',e';s',f')]\}$$

Subject to:

$$\begin{aligned} c = ws + (p^h + p^e e)H(h,f,i,e) + (1+r)b - \Phi^H(h',h) - \Phi^E(e',e,h) \\ - (p^h + p^e e')h' - b' + I(h,f,i,e) \end{aligned}$$

$$b' \geq \underline{\mathrm{b}}$$

Where the remaining housing from the previous period is:

$$H(h,f,i,e) = (1 - f * \tau^f(1-\tau^e e))(1-\delta)h$$

The net payment from insurance is:

$$I(h,f,i,e) = i(\underbrace{f\tau^f(1-\tau^e e)(p^h+p^e e)}_{\text{Insurance payout}} - \underbrace{q\rho^f\tau^f(1-\tau^e e)(p^h+p^e e)}_{\textit{Premium}})(1-\delta)h$$

Adjustment costs for changing housing are kinked and convex in the spirit of Kaplan, Moll, and Violante (2018), here following the specification in Auclert, Bardóczy, Rognlie, and Straub (2021):

$$\Psi^H(h', h) = \frac{\chi_1}{\chi_2} \left| \frac{h' - (1-\delta)h}{(1-\delta)h + \chi_0} \right|^{\chi_2} [(1-\delta)h + \chi_0],$$

with $\chi_0, \chi_1 > 0$ and $\chi_2 > 1$..

Adjustment costs from changing elevation are linear in housing:

$$\Phi^e(e', e, h) = \chi^e \mathbb{1}(e \neq e')H(h, f, i, e)$$

And utility is CRRA:

$$u(.) = \frac{.^{1-\sigma}}{1-\sigma}$$

Envelope conditions Defining the following FOC:

$$H_h(h, f, i, e) = (1 - f * \tau^f(1 - \tau^e e))(1 - \delta)$$

$$I_h(h, f, i, e) = i\tau^f(1 - \tau^e e)(p^h + p^e e)(1 - \delta)(f - q\rho^f)$$

$$\Phi_h^E = \chi^e \mathbb{1}(e \neq e')H_h(h, f, i, e)$$

Then the envelope conditions are:

$$\begin{aligned} &V_c = u'(c) \\ &V_h = u'(c)[(p^h + p^e e)H_h(h, f, i, e) - \Phi_2^H - \Phi_h^E + I_h(h, f, i, e)] + u'(H)H_h(h, f, i, e) \end{aligned}$$

First-order conditions Where λ is the Lagrange multiplier on the borrowing constraint, the FOC with respect to b' and h' are:

$$\begin{aligned} u'(c) &= \lambda + \beta \mathbb{E} \partial_{b'} V(b', h', i', e'; s', f') \\ u'(c)((p^h + p^e e') + \Phi_1^H) &= \beta \mathbb{E} \partial_{h'} V(b', h', i', e'; s', f') \end{aligned}$$

Solution method To address the number of exogenous, discrete, and continuous states and choices in the model, I split the households decision problem into a series of stages, as suggested by Druedahl (2021) and outlined by Auclert, Bardóczy, Rognlie, and Straub

(2021). The above outline of the household problem reflects the choices at stage (4), after elevation and insurance decisions and exogenous states are realised.

Timing and solution method for the household decisions:

1. Insurance i decision

   Solved as a discrete choice problem, solved using extreme value taste shocks following the approach of Auclert, Bardóczy, Rognlie, and Straub (2021).

2. Elevation e decision

   Solved similarly to the insurance choice as a discrete choice problem, using extreme value taste shocks.[24]

3. Realisation of exogenous states s, f

4. Housing and consumption h', c, b' decision.

   This is solved in a similar manner to the proposed solution to the two-asset problem in Auclert, Bardóczy, Rognlie, and Straub (2021), using the first-order and envelope conditions above. The first order conditions can be combined into two expressions:

$$\text{Unconstrained:} \qquad \frac{\mathbb{E}\partial_{h'}V(b', h', i', e'; s', f')}{\mathbb{E}\partial_{b'}V(b', h', i', e'; s', f')} = (p^h + p^e e') + \Phi_1^H(h', h)$$

$$\text{Constrained:} \qquad \frac{\beta\mathbb{E}\partial_{h'}V(\underline{\text{b}}, h', i', e'; s', f')}{\lambda + \beta\mathbb{E}\partial_{b'}V(\underline{\text{b}}, h', i', e'; s', f')} = (p^h + p^e e') + \Phi_1^H(h', h)$$

   Solving these in sequence for the policy functions for h, b, c for both constrained and unconstrained cases is similar to Auclert, Bardóczy, Rognlie, and Straub (2021), and using the constrained policy functions wherever the unconstrained bond policy function would violate the borrowing constraint.

   However, the first-order conditions are necessary, but not sufficient when combined with the discrete choices on insurance and elevation. To accommodate for this, I use an upper envelope algorithm which takes the policy function for bonds implied by the first-order conditions, and searches over all bond choices available (given a particular set of exogenous states, discrete choice decisions on insurance and elevation and corresponding housing policy functions) to see if an alternative bond choice would return higher utility.

[24] To account for the adjustment cost, also create a phantom state e_{old} (not laid out explicitly in the main household problem) which stores the previous period's elevation decision. This is implemented adding a large negative utility value if $e_{old} \neq e_{-1}$.

This approach assumes that the mapping between bond and housing decisions is the same for all alternatives.

I use the SSJ approach of Auclert, Bardóczy, Rognlie, and Straub (2021) to solve for house prices. Formally, I solve for a non-linear transition from the original steady state, and for numerical practicality I simulate a rise in flood risk and an eventual return back to the original flood risk, after a long-enough period in the higher flood risk that a new steady state is reached.

The numerical parameters used for the solution are summarised in D.1.

Table D.1: Numerical parameters

Parameter	**Value**	**Description**
n_e	4	Number of productivity states
bmax	10	Maximum bond holdings
bmin	-0.1	Borrowing constraint
hmax	10	Maximum housing holding
kmax	10000	Additional numerical grid calibration
n_b	80	Number of points on bond grid
n_h	110	Number of points on housing grid
Taste shock variance	1e-5	Chosen to ensure it doesn't affect elevation and insurance choice
SS tol	1e-4	Convergence of SS
GE tol	1e-6	Max housing market error in transition

D.2 Additional results

This section shows additional model results, described in the main text. Figures D.2 and D.3 show example and average policy functions. Where discontinuous, this is sometimes due to the jump-y nature of flood risk causing large reductions in housing value and resulting spikes the distribution and policy functions.

Figure D.1: Projected changes in the frequency of extreme precipitation vs 1850–1900 - IPCC (2021)

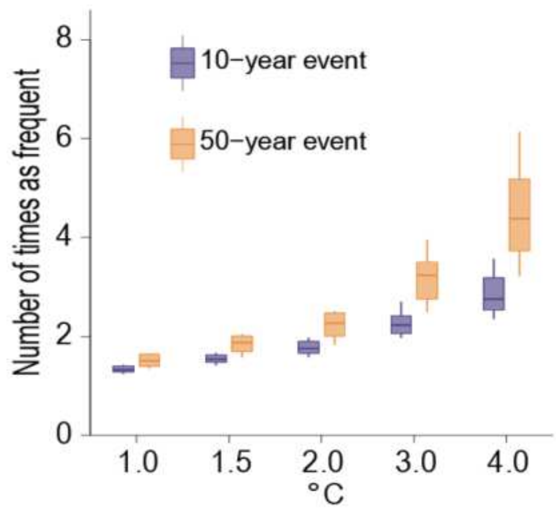
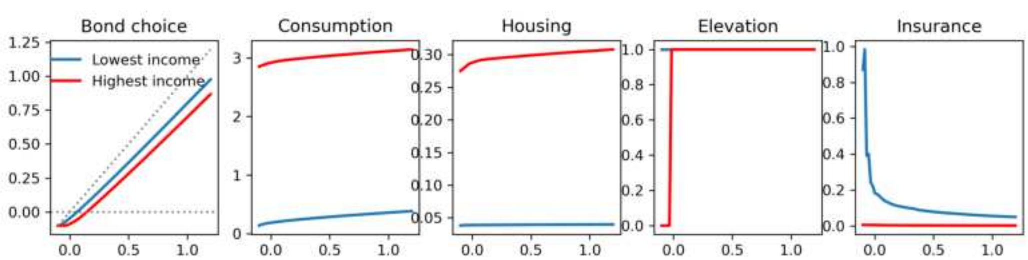
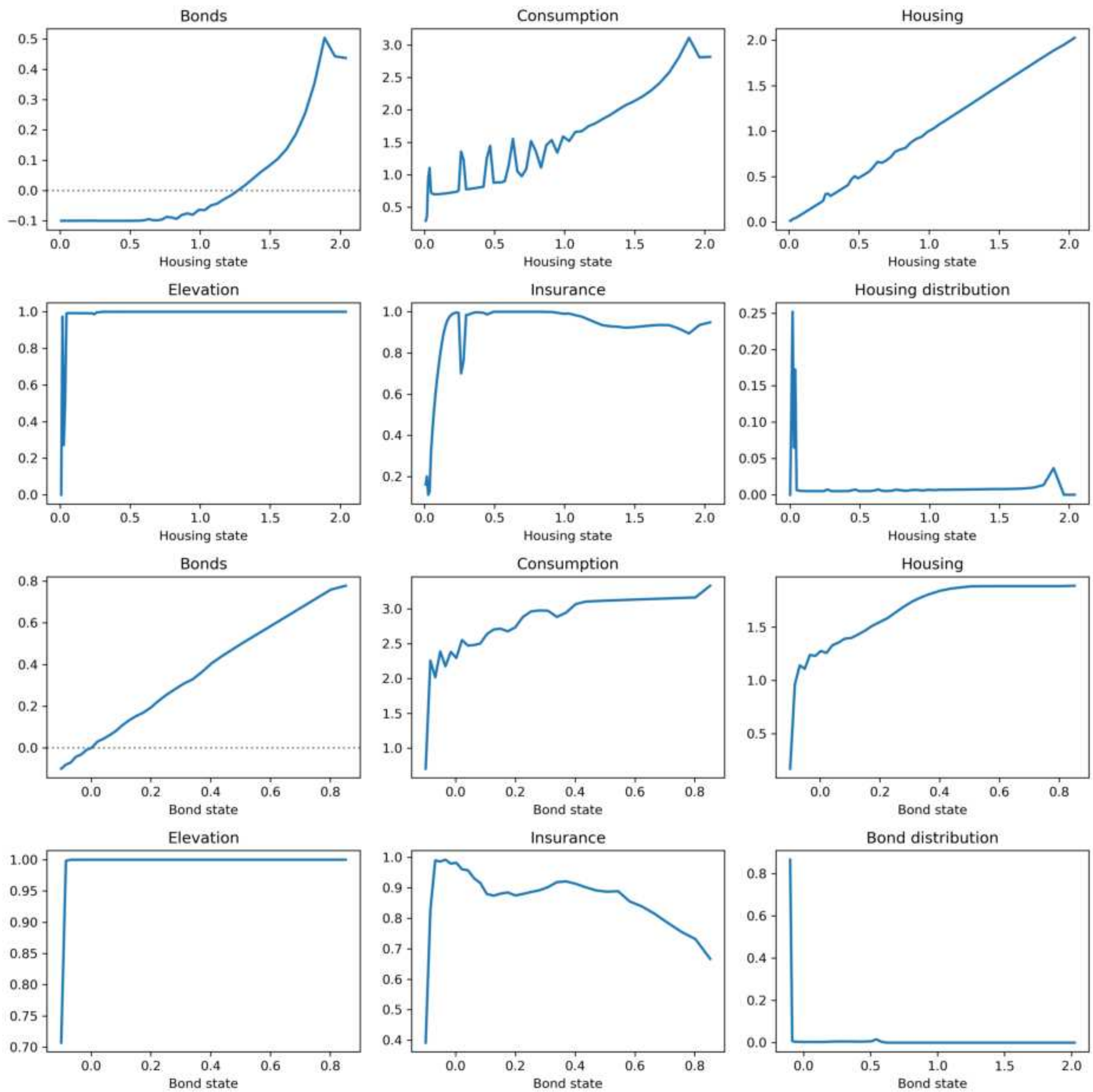


Figure D.2: Example policy functions



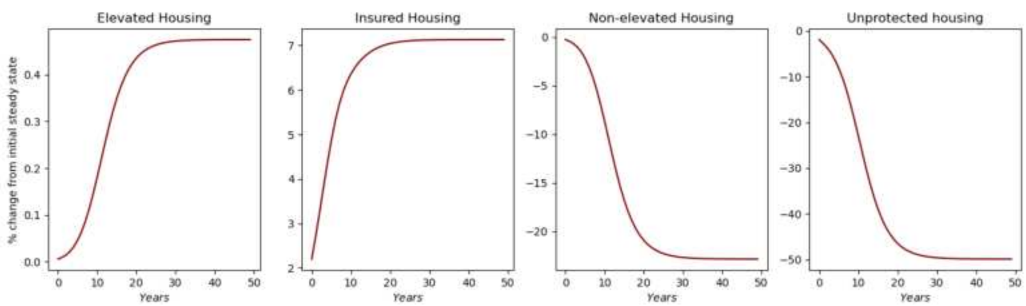
Notes: Policy function for a household who previously had an elevated home, was uninsured and had a low housing state. Decisions shown across previous bond state of the household.

Figure D.3: Average policy functions

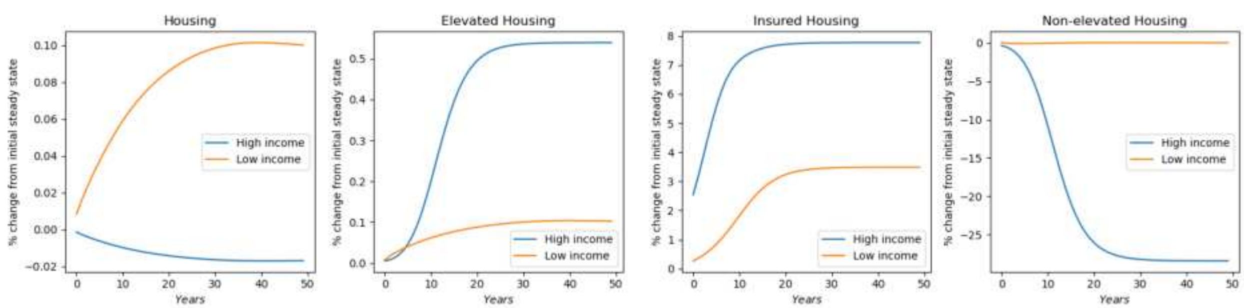


Notes: Average decisions for households across housing and bond states, along with the housing and bond distribution in steady state.

Figure D.4: Housing changes following rise in flood risk



(a) Average



(b) Across incomes

Notes: Model transition path following an increase in flood risk shown in Figure 9. Panel D.4a shows the average change in housing of different types. Unprotected housing is neither insured nor elevated. Elevated houses can also be insured and vice versa. Panel D.4b shows the corresponding averages for portions of the income distribution.