Residential-Mobility Responses to Home Damage Caused by Floods, Cyclones and Bushfires in Australia

Abstract: Recent climate disasters serve as a reminder of the growing—yet overlooked—risk of climate-driven displacement in the Global North. This paper contributes to a nascent literature on disaster-induced mobility in high-income countries by extending the evidence to a new context: Australia. Applying propensity score matching to panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, we conduct the first causal assessment of the impact of home damage caused by extreme weather events on residential mobility in Australia. Our findings suggest that from 2009 to 2022 an annual average of 1.6% of Australians aged 15+ (or ~308,000 people a year) experienced home damage caused by floods, cyclones or bushfires. Such damage increases the probability of changing address within one year by 56%, displacing an annual average of 22,261 Australians. Cumulatively, this amounts to ~312,000 people displaced by climate-induced home damage between 2009 and 2022. Importantly, this type of climate-induced mobility is not evenly spread across the population. Contrary to findings from the Global South, we find no evidence of "entrapment effects", except for uninsured homeowners. Instead, our results indicate that over 80% of climate-displaced Australians come from the bottom two income quartiles, with the poorest 3% accounting for 14% of the displaced population. The most disadvantaged Australians thus face a double vulnerability: they are both more likely to sustain home damage from extreme weather events, and more likely to be displaced. These findings bear important implications for adaptation strategies and policy responses to natural disasters.

Keywords: climate change; disasters; inequalities; residential mobility; internal migration, propensity score matching

1. Introduction

With climate change leading to more frequent and severe extreme weather events (AghaKouchak et al. 2020), disaster-induced population movement is becoming a topic of growing interest within academic, media and policy circles. Although the scale of the phenomenon is difficult to assess (Beyer, Schewe, and Abel 2023; Hugo 1996), there are numerous examples of large-scale displacement following floods, wildfires and cyclones. For example, over 500,000 people were displaced after Hurricane Katrina in 2005 (Gabe et al. 2005) and 7 million people following the Pakistani floods of 2010 (Din 2010). There is broad consensus that the impact of natural hazards on residential mobility tends to be short-lived and occurs over short distances (Black et al. 2011; Findlay 2011). This occurs because most disaster-affected residents express a desire to stay in their places of residence (Tinoco 2023; Berlin Rubin and Wong-Parodi 2022; Sharygin 2021), a preference often reinforced by reconstruction activity and policy (Huang et al. 2022). Yet there are historical cases of settlement abandonment (McLeman 2011; Greenberg, Lahr, and Mantell 2007) and long-distance population movement (Graif 2016; Fussell, DeWaard, and Curtis 2023) following extreme weather events. This goes to show the diversity of mobility responses to natural hazards, and how these can occur at a range of spatial and temporal scales (Black et al. 2013).

There is also growing recognition that exposure to extreme climate events is not randomly distributed within the population. Rather, low-income and minority populations are often concentrated in areas more prone to natural hazards (such as floodplains) or regions with poor environmental conditions (Tierney 2020). These spatio-structural inequalities became clear after Hurricane Katrina hit New Orleans in 2005. Because of land-development and residential-segregation patterns, low-income groups and African Americans were disproportionally concentrated in low-lying suburbs and consequently reported higher levels of home damage and higher odds of relocation (Fussell, Sastry, and VanLandingham 2010). The hazard-exposure-vulnerability framework (McLeman et al. 2021) conceptualises some of these processes by proposing that climate and environmental risks are shaped by: (a) the nature of specific climatic hazards, (b) the exposure of people, resources and systems to such hazards, and (c) their vulnerability. Thus, some conditions, such as poverty and inadequate infrastructure, increase the likelihood of being adversely affected by climate-induced hazards (IPCC 2014). In the context of residential relocation, individuals from less advantaged socio-economic groups, for example, tend to have less robust housing and lack access to emergency services and information. These disadvantages compound with one another, exacerbating the risk of experiencing home damage when disaster strikes and the ensuing likelihood of subsequent relocation. In other words, disaster-induced relocations are rooted in broader social structures and power dynamics (Tierney 2020).

While evidence from the Global North—largely drawn from the United States—indicates an increased risk of residential mobility following an environmental disaster, particularly amongst disadvantaged groups, research on the Global South is both greater in volume and more mixed in its findings. Evidence from the Global South shows that rapid-onset climatic disasters can reduce population movement by constraining households' resources (Mueller, Gray, and Kosec 2014), leading to the entrapment of the most vulnerable populations, especially those in the poorest regions (Nawrotzki and DeWaard 2018; Black et al. 2013). Empirically, this manifests in a negative relationship between income and the probability of moving following extreme climate events (Mueller, Gray, and Hopping 2020; Cattaneo et al. 2019). This again highlights the diversity of population movement responses to extreme weather events, which are contingent on the vulnerability of both people and places (Black et al. 2013). Mobility decisions are indeed known to be context-specific and shaped by broader societal conditions, which influence the resources and adaptative capacity of communities affected by climate hazards (Ronco et al. 2023). For example, floods generate higher levels of internal displacement in countries with non-democratic governance, armed conflict, and low GDP (Vestby et al. 2024; Hoffmann et al. 2023; Beine and Parsons 2017). The higher level of disaster-induced displacement in low- and middle-income countries explains the focus of most contemporary climate-migration research on the Global South compared to the Global North (Barbier and Hochard 2018).

However, as climate change intensifies, we argue that evidence needs to be broadened to countries of the Global North. Indeed, recent weather-related disasters have highlighted substantial vulnerabilities and ensuing population displacement in wealthier and more technologically advanced nations (Black et al. 2013; Muttarak 2021). This includes evidence from Hurricane Katrina in the United States (2005) and Hurricane Maria (2017) in Puerto Rico (Alexander, Zagheni, and Polimis 2019; Fussell, Sastry, and VanLandingham 2010) and the 2013/2014 floods within central Europe (Župarić-Iljić 2017; Grams et al. 2014). Similarly, the 2017 California bushfires led to an increase in relocation intentions (Tinoco 2023). Altogether, research on high-income countries is scarcer than on low-income countries, and it remains largely confined to the United States (Cipollina, De Benedictis, and Scibè 2023; Piguet, Kaenzig, and Guélat 2018). In this study, we extend the evidence base to a new high-income country: Australia.

Australia constitutes an interesting case study, as its climate is strongly affected by the surrounding oceans and the El Niño-Southern Oscillation (ENSO) phenomenon (IPCC 2022). This leads to repeated floods and prolonged droughts. Examples of recent extreme weather events in Australia include the 2019/2020 megafires that killed 450 people, both directly and indirectly as a result of smoke inhalation (Johnston et al. 2021) and cost around AUS$100 billion (Read and Denniss 2020), and the 2021 and 2022 floods in eastern Australia—the most widespread and costly floods in the country's recorded history (Fryirs et al. 2023). Australia faces projected increases in the intensity of cyclones, sea-level rise, and localised high-intensity rainfall, which are in turn expected to lead to greater flood damage and storm-surge height in some areas and significant decreases in rainfall in others (IPCC 2022). Despite the existence and aggravation of extreme weather conditions in Australia, research has rarely considered their impacts on population displacement and existing evidence is largely qualitative. Here, we provide novel causal estimates of the level of population displacement associated with home damage caused by rapid-onset climate events in Australia. In doing so, we address three allied research questions: (i) which population groups are more likely to be affected by home damage due to extreme weather events?, (ii) which population groups are more likely to move as a result?, and (iii) do these moves exhibit distinct spatial and temporal patterns?.

To answer these questions, we draw on panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey—a nationally-representative household panel of the Australian population aged 15 and over. We focus on the 2009 to 2022 period, when a question on home damage from extreme weather events (e.g., floods, cyclones and bushfires) was included. The HILDA Survey provides a unique opportunity to accomplish our research aims: it captures population movement at a range of spatial and temporal scales; it collects rich information on respondents' socio-demographic characteristics; and includes an annual question rarely collected in national surveys on home damage caused by floods, cyclones and bushfires in the last 12 months. Because the question does not differentiate between different types of natural hazards, we analyse the joint impact of home damage due to floods, cyclones and bushfires on residential mobility.

Given the challenges associated with climate-induced population movement, providing robust evidence that enables appropriate policy response and anticipatory action for future disaster is paramount (Beyer, Schewe, and Abel 2023). However, attempts at drawing robust estimates have been hindered by the fact that exposure to extreme weather events is not random (Fussell, Sastry, and

VanLandingham 2010). Here, we overcome this issue by leveraging a Propensity Score Matching (PSM) methodology (Stuart and Rubin 2008) that adjusts the estimates for selection into experiencing home damage due to rapid-onset climate events, yielding more reliable estimates of its causal effect on residential mobility. In doing so, it is important to note that our focus is on establishing the direct impact on residential mobility of *home damage* caused by disasters. As we discuss later, the overall effect of disasters on residential mobility may be greater, encompassing also indirect impacts operating, for example, through damage to infrastructure, changes in risk perceptions, shifting locational preferences, or job losses.

2. Data and Methods

2.1. The Household Income and Labour Dynamics in Australia (HILDA) Survey

We harness 14 years of panel data from the HILDA Survey, a high-quality, multipurpose study collecting longitudinal information from Australian households since 2001 (Watson and Wooden 2012). Based on a complex probabilistic sampling design, the HILDA Survey is representative of the Australian population aged 15 and older. Further, the survey boasts a high wave-on-wave retention rate, of 90-95% (Summerfield et al. 2021). As a result, panel attrition has had a limited impact on internal migration estimates using the HILDA Survey (Sander and Bell 2014), which are comparable to those from the national population census (Watson 2020; Kalemba et al. 2022). Indeed, the HILDA Survey has been used widely used in internal migration and residential mobility research for a broad range of topics, including trends in and determinants of population movement (Campbell 2019; Crown, Gheasi, and Faggian 2020; Perales and Bernard 2023), its social and economic impacts (Clark and Lisowski 2019; Korpi and Clark 2017), and its associations with life-course transitions (Clark and Lisowski 2018; Bernard, Bell, and Charles-Edwards 2016; Vidal et al. 2017; Sander and Bell 2014).

Since 2009, HILDA Survey respondents have been asked the following question on an annual basis: “In the last 12 months, has a weather-related disaster (e.g., flood, bushfire, cyclone) damaged or destroyed your home?”. We use responses to this survey item to derive a variable capturing home damage due to extreme weather events (i.e., floods, cyclones and bushfires) (‘yes’/‘no’). This survey item has been previously used to establish the impact of extreme-weather-related home damage on health and well-being (Li, Toll, and Bentley 2023; Gunby and Coupé 2023). To our knowledge, it has never been used to assess the impact of home damage caused by extreme weather events on residential mobility. This represents the key aim of the present study. It is important to acknowledge that, in using this survey item, we only focus on the direct impact of disasters caused by home damage and do not consider the indirect impacts of exposure to disasters on residential mobility—such as damage to infrastructure (e.g., roads and schools), changes in risk perceptions, shifts in locational preferences, and job loss. In addition, this survey item does not allow us to distinguish between the type of natural hazard or to ascertain the degree of damage a home sustained during a weather event. We return to these points in the discussion section.

Climate-induced home damage is one of multiple life-course events for which information is collected annually within the HILDA Survey, along with others such as marriage, pregnancy/childbirth, separation, employment loss, and retirement. To benchmark the impact of climate-induced home damage on residential mobility, we compare its estimated effect to those of these well-established relocation triggers (Bernard, Bell, and Charles-Edwards 2014; Rindfuss 1991; Mulder 1993).

For our purposes, we define residential mobility as a change of address between two consecutive survey waves within an unbalanced panel structure. This information is obtained from an annual binary question: "did you change address of residence in the last 12 months" ('yes'/'no'). Between 2009 and 2022, an annual average of 12.81% of the Australian population aged 15+ years changed address. The annual average for those who experienced climate-induced home damage was 19.47%, suggesting that this event may be a trigger of residential mobility. However, careful modelling is required to draw firm conclusions, as we discuss in the next section.

3.2 Estimation Strategy

The analysis proceeds in three sequential steps. First, we calculate the annual share of the Australian population exposed to extreme-weather related home damage. We do so for unbalanced sample of 192,790 person-year observations from 23,522 individuals. By applying population weights derived by the HILDA Survey team (Summerfield et al., 2021), we report results that are nationally representative.

Second, we use a logistic regression model to identify the determinants of extreme-weather-related home damage in Australia. The explanatory variables include an encompassing range of economic, demographic, locational, and social characteristics used in previous studies (Perales and Bernard 2023; Korpi and Clark 2017; Pelikh and Kulu 2018). These include respondents' age, gender, immigrant status, marital and parental statuses, household income, educational attainment, duration of residence, state of residence, survey year, and metropolitan status. We also consider housing tenure, distinguishing between renters, insured homeowners, and uninsured homeowners.[1] Appendix A presents descriptive statistics on all analytic variables. To accommodate repeated observations from the same individuals and account for the nesting of individuals within households, the model's standard errors are clustered on both individuals and households.

Finally, we estimate the impact of extreme-weather-related home damage on changes of address within the year. Given the possible endogeneity of experiencing home damage caused by extreme weather events, we use a matching approach to reduce selection bias. There is no consensus on the best method, but matching techniques aim to maximise balance between the treated group (home damage) and the control group (no home damage) on the pre-treatment variables and minimise the number of observations removed from the dataset (King et al. 2011). To select the most suitable approach for the data at hand, we assess four well-established methods by: (i) comparing the number of observations kept post-matching, and (ii) the balance between the treated and control groups, which we measure as the mean absolute standardised difference across all covariates (see King and Nielsen 2019). Following best practice in quasi-experimental designs, we include a large set of covariates that are associated with the exposure and outcome variables—namely, all variables used as predictors in the logistic regression model described before. The results in Table 1 show that all matching methods improve the balance between the treated and untreated groups. While Coarsened Exact Matching (CEM) performs the best in terms of balance, it reduces the sample size by over 25%. This is a known problem that has led some authors to caution against the use of CEM despite its desirable statistical properties (Iacus, King, and Porro 2012), particularly when using datasets with rich covariate information (Ripollone et al. 2020; Wang 2021) as is the case here. In contrast, Propensity Score Matching (PSM) offers the second-best balance after CEM without reducing the sample size.

[1] As a caveat, the insurance question in the HILDA Survey combines vehicle, home and content insurance. Therefore, we define uninsured homeowners as individuals with zero expenditure on these three insurance types combined.

Although PSM has been criticised for reliance on model specifications and risk of biased estimates when the model is misspecified (King and Nielsen 2019), we found that it yields the optimal bias-variance trade-off for our data and therefore opt for this matching technique for our analyses. The results are reported as Average Treatment Effects (ATEs), which denote the difference in residential mobility between the treated (home damage) and control (no home damage) groups after balancing the covariates between the two groups, expressed in percentage points, making the comparison closer to a randomised experiment**.**

[TABLE 1]

To detect heterogeneity in mobility responses to extreme weather events and better understand the temporal dynamics of disaster-induced residential mobility, we replicate the PSM analysis at different spatial and temporal scales. We do so by measuring residential mobility using different distance thresholds. For each change of address, the distance moved is calculated based on the great circle formula (Thomas, Gillespie, and Lomax 2019), which accounts for the curvature of Earth (Small 2012). Given the vast scale of Australia, this approach is more accurate than a basic Euclidean distance calculation, which gives a straight-line distance and ignores the spheric shape of Earth. From this variable, we construct 20 overlapping distance-based measures of population movement, ranging from 'up to 1 kilometre' to 'up to 350 kilometres'. Given that most moves occur over short distances (Lomax, Norman, and Darlington-Pollock 2021; Thomas, Gillespie, and Lomax 2019), we define shorter distance-based measures of mobility in 5-kilometre increments from 5 kilometres to 65 kilometres since 65 kilometres is the threshold at which employment reasons begin to outweigh housing reasons for moving in Australia (Thomas, Gillespie, and Lomax 2019). We then use 10-kilometre increments from 70 kilometres to 100 kilometres, followed by moves up to 200 kilometres and 350 kilometres.

We then measure residential mobility at four different observation intervals: the year disaster-induced home damage occurred and up to three years later in one-year increments. We derive these measures by comparing the census collection district of residence the year before home damage occurred to the census collection district of residence 1, 2, and 3 years later. The census collection district is the finest geographic scale at which place of residence is made available in the HILDA survey. The 38,700 census collection districts that cover Australia comprise an average of 255 dwellings and are analogous to census tracks in the United States.

Finally, we replicate the PSM analysis of our key residential mobility measure (i.e., change of address in the last 12 months) for different subpopulation groups. Specifically, we distinguish between homeowners (with and without insurance) and renters, as well as between low- and high-income households. We assess differences between these groups by comparing the magnitude of the estimated impact of climate-induced home damage (i.e., whether it increases or decreases residential mobility) and the overlap (or lack of thereof) in confidence intervals. The focus on housing tenure is motivated by: (i) our event of interest (i.e., disaster-induced home damage) being tightly connected to house ownership; (ii) well-established findings in both the voluntary and forced mobility literatures that renters are more mobile than homeowners (Clark and Lisowski 2019), and (iii) recent research indicating that flood insurance payouts ground people in place (Rhodes and Besbris 2022a). We also explore variations by socio-economic status, using both self-reported and income-based measures, because of the greater vulnerability of disadvantaged groups to extreme weather events as discussed in Section 2.

4. Empirical Evidence

4.1 Level and Determinants of Exposure to Climate-Induced Home damage

We begin our empirical analysis by ascertaining the annual share of individuals affected by home damage due to extreme weather events. From our weighted sample, we find that between 2009 and 2022, an average of 1.57% of the Australian population aged 15+ years was affected by extreme weather-related home damage every year. At the population level, this corresponds to an annual average of 308,133 individuals affected during the observation period.

The multivariate logistic regression model in Table 2 identifies the individual and household-level factors associated with exposure to extreme-weather-related home damage. To facilitate interpretation, the model parameters are presented as both odds ratios (ORs) and predicted probabilities (PPs), with covariates held at the sample mean. The results show a socio-economic gradient in exposure to climate-induced home damage. All else being equal, sampled individuals in the top (OR=0.89, p>0.10, PP=1.53%) and second-top income quartiles (OR=0.91, p>0.10, PP=1.57%) are significantly less likely to be affected than individuals in the bottom income quartile (PP=1.72%). However, these income-quartile differences were not statistically significant and thus not extrapolatable to the population. To further explore this socio-economic gradient, we replaced income quartiles with a self-reported measure of economic prosperity based on a five-point scale: 'very poor', 'poor', 'just getting along', 'reasonably comfortable' and 'very comfortable'.[2] The results in Appendix C confirm an increased risk of climate-induced home damage among the most disadvantaged groups, with the differences being statistically significant. *Ceteris paribus*, the probability of experiencing climate-induced home damage is 3.63% and 3.14% for individuals self-classifying as 'very poor' and 'poor', respectively, compared to 1.45% and 1.29% for those self-classifying as 'reasonably comfortable' and 'very comfortable'.

In contrast, tertiary-educated individuals[3] (OR=0.85, p<0.01, PP=1.43%) are significantly less likely to be exposed to home damage than non-tertiary-educated individuals (PP=1.67%).[4] Concerningly, insurance coverage also appears to be a strong independent determinant of exposure (OR=1.57, p<0.001). *Ceteris paribus*, uninsured homeowners have a 2.37% chance of experiencing extreme weather-related home damage compared to 1.63% among insured homeowners. This may be due to increasing premiums on climate-unsafe areas coupled with the emergence of uninsurable 'danger' zones (CCA 2022).

Age and life-course stage also seem to exert significant influences on the propensity to sustain climate-induced home damage. For example, parents with dependent children (OR=1.18, p<0.05, PP=1.70%) are more likely to be affected than individuals without children (PP=1.45%), whereas individuals aged over 65 years (OR=0.79, p<0.05, PP=1.13%) are significantly less likely. In addition, longer durations of residence are significantly associated with a lower likelihood of sustaining climate-induced home damage. However, we observe no significant differences between renters and insured homeowners or between native and foreign-born individuals. These variations are overlaid by broader spatial inequalities. Specifically, individuals in non-metropolitan Australia and those in Queensland, New

[2] Descriptive statistics in Appendix A show that 52.3% of respondents self-classify as being 'reasonably comfortable', followed by 25.5% as 'just getting along' and 18.9% as 'very comfortable'. Meanwhile, the most vulnerable groups, 'poor' and 'very poor', account for 2.5% and 0.7% of the sample.

[3] This corresponds to college / university education in the United States.

South Wales and the Northern Territory are significantly more likely to be exposed to home damage due to extreme weather events, all else being equal.

Overall, these results point to systematic differences in the propensity for different population groups to sustain home damage from extreme climate events, with some vulnerable groups being comparatively overexposed. This pattern of results underscores the usefulness of applying PSM techniques to obtain robust estimates of climate-induced residential mobility in Australia.

[TABLE 2]

4.2 Climate-Induced Home damage and Residential Mobility

Having examined the extent and determinants of climate-induced home damage in Australia, we now analyse its impacts on residential mobility using a PSM methodology. We express the results using average treatment effects (ATEs), which represent the average difference in residential mobility between the treated (i.e., individuals who experienced home damage caused by extreme weather events) and the untreated (i.e., individuals with no such experience) after balancing the covariates between the two groups, expressed in percentage points. The estimated ATE for climate-induced home damage amounts to 0.073, indicating that—on average—having sustained extreme-weather-related home damage increases the odds of moving by 7.28 percentage points within a year (95% confidence interval [CI]: 5.22–9.34 percentage points), which corresponds to a 56% increase. Considering the exposure rate to climate-induced damage, we infer that—at a population level—an average of 22,261 Australians aged 15+ were displaced every year between 2002 and 2009 (95% CI: 15,952–28,561). This corresponds to 0.87% of all changes of address recorded in Australia during this period.

To further contextualise the magnitude of the reported effect, we applied an analogous PSM approach to identify the impacts of other life-course events on the propensity to migrate. These additional analyses, shown in Figure 1, reveal that the estimated effect of climate-induced home damage on residential mobility (+7.28 percentage points; 95% CI: 5.22–9.34 percentage points) is comparable to those of other life-course events that have received greater scholarly attention. This is the case for marital separation (+10.24 percentage points; 95% CI: 7.77–12.70 percentage points) and childbirth (+5.78 percentage points; 95% CI: 3.51–8.05 percentage points), which exhibit overlapping confidence intervals with climate-induced home damage. Importantly though, the estimated effect of climate-induced home damage is greater than those of job loss (+1.82 percentage points; 95% CI: 0.55–3.09 percentage points), and retirement (not statistically different from zero) and marriage (not statistically different from zero). This finding serves to highlight the importance of considering climate events in residential-mobility research.

[FIGURE 1]

4.3 Spatio-Temporal Dynamics

To assess how far people move, we replicate the PSM analysis for climate-induced home damage using different mobility-distance thresholds. Results in Figure 2a reveal a strong distance decay, with most moves motivated by climate-induced home damage occurring over short distances. This finding is consistent with well-established patterns in the residential mobility (Stillwell et al. 2016) and environmental mobility (Piguet, Pécoud, and De Guchteneire 2011) literatures. More specifically, the odds of moving following climate-induced home damage decrease rapidly from 1 kilometre (ATE=0.069) to 25 kilometres (ATE=0.016), after which the ATEs stabilise. Because 65 kilometres is the distance at which mobility begins to affect social networks in Australia (Lomax, Norman, and Darlington-Pollock 2021), we conclude that most climate-induced moves are short-distance and do not disrupt the social networks of disaster-affected residents.

Next, we analyse temporal dynamics by tracking respondents' census collection district of residence for up to three years after home damage due to an extreme weather event was recorded. Results in Figure 2b show a rapid decrease in the odds of living in a new location over time. However, the impact of home damage remains statistically significant, which indicates that up to three years after the event some residents are still displaced. Importantly, the level of residential mobility stabilises after one year, with ATEs ranging from 0.023 to 0.032. This pattern of results indicates that approximately 40% of individuals who moved following climate-induced home damage were still living in a different census collection district three years on[5]. It also suggests that the majority of impacted residents returned within 12 months, yet results remain tentative due to large and overlapping confidence intervals.

[FIGURE 2]

4.4 Socio-Economic Gradient in Residential Mobility Reponses to Climate-Induced Home damage

To capture possible heterogeneity between sub-population groups in residential mobility responses to climate-induced home damage, we replicate some of the analyses presented above by key population groups. For parsimony, these subgroup analyses are based on the most granular change-of-address measure of mobility recorded the year of a disaster. Since the risk of sustaining climate-induced home damage was shown to vary by housing tenure, insurance coverage and socio-economic status (see Table 2), the analyses in this section focus on those variables.

Consistent with expectations, the estimated effect of climate-induced home damage on residential mobility is larger for renters (ATE=0.17) than homeowners (Figure 3a). This is consistent with the well-established finding in the broader residential-mobility literature that home ownership constrains mobility by increasing the costs of moving (Jia et al. 2023). There are, however, notable differences between homeowners depending on their insurance coverage. Of particular concern is the negative ATE for uninsured homeowners (ATE=–0.031), for whom experiencing climate-induced home damage decreases the odds of moving. In comparison, the ATE for insured homeowners is positive (ATE=0.020). This pattern of effects signals a possible risk of "entrapment" for uninsured individuals (Rhodes and Besbris 2022a), who may neither have the means to move nor to rebuild their homes.

Analogous analyses by income quartiles in Figure 3b reveal that low-income earners from the bottom two quartiles (ATEs=0.075 and 0.139, respectively) are more likely to be displaced when experiencing climate-induced home damage than high-income earners (ATEs=0.026 for the top two income quartiles). The ATEs are not statistically significant for individuals within the top two income quartiles, which means that, on average, high-income earners do not move when experiencing home damage.

[5] We obtain this estimate by dividing the ATE the year of housing damage (0.068) by the ATE three years later (0.028). Note that the ATE recorded the year of the housing damage (0.068) is lower than the ATE recorded in Section 4.2 (0.073) because here we measure change of census collection district and not change of address, but is on par with the estimate for changes of address up to 1 km (0.069).

We also replicated the analyses using the self-reported measure of economic prosperity based on a five-point scale, with even more patterned results (see Figure 3c) confirming significant socio-economic inequalities in the risk of displacement. Specifically, the estimates reveal a linear trend, from an ATE of 0.215 for individuals who self-identify as 'very poor' to an ATE of 0.029 for individuals who self-identify as being 'very comfortable'. For the latter group, the ATE is not statistically significant, indicating that their propensity to move is not affected by climate-induced home damage.

[FIGURE 3]

4.5 The Uneven Burden of Climate-Induced Home damage

To obtain a full picture of how climate-induced displacement affects individuals from different socio-economic strata, Figure 4 juxtaposes the results in the previous section against the results for the risk of exposure presented earlier. The X-axis shows the predicted probability of exposure to climate-induced home damage by self-reported socio-economic status, whereas the Y-axis shows the average treatment effect of climate-induced home damage for each group. Both axes intersect at the sample mean, with the bubble size representing the share of each group in the population.

The relative location of the different socio-economic groups clearly demonstrates that climate events hit the most vulnerable hardest. All else being equal, socio-economically disadvantaged groups are both at a greater risk of sustaining climate-induced home damage and at a greater risk of being displaced (net of the effect of differences in socio-demographic attributes). For those self-classifying as being 'very poor', the predicted probability of experiencing climate-induced home damage is 3.6% and the likelihood of being displaced as a result is 21.5 percentage points higher. Similarly, 3.1% of those self-classifying as 'poor' experience climate-induced home damage and the odds of being displaced as a result 17.2 percentage points higher. In contrast, people self-classifying as 'very comfortable' are nearly three times less likely of being exposed (1.3%) and 7 times less likely to be displaced (2.9 percentage point increase in residential mobility). The most disadvantaged Australians thus face a "double vulnerability": they are both more likely to sustain home damage from extreme weather events, and more likely to be displaced as a result.

Using the information in Figure 4, it is possible to compare the share of the overall and displaced populations by their self-reported socio-economic status. Results in Appendix D show that the bottom 3% of Australians account for 14% of the population displaced due climate-induced home damage, while the top 19% of the population account for just 5% of those displaced. Results by income quartile confirm the existence of substantial socio-economic inequalities. The bottom two income quartiles represent 50% of the total population but 80% of the displaced population, whereas the top two income quartiles represent 50% of the total population but just 20% of the displaced.

[FIGURE 4]

5. Discussion and Conclusion

In response to calls to expand the geographic coverage of research on population movement caused by natural hazards (Piguet et al. 2018), this paper has provided the first casual estimate of the level of residential mobility triggered by home damage caused by sudden-onset climate events in Australia.

The choice of case-study country was motivated by the scale of extreme weather events in Australia, where floods, wildfires and cyclones are increasing in intensity (BOM and CSIRO 2022) and by access to high-quality, nationally representative panel data. Our findings confirm four well-established patterns, while providing new insights for a high-income country context, with ensuing implications for policy and future research.

First, our findings confirm that most housing-damage-induced moves take place over short distances and, thus, do not significantly disrupt social networks. We found that experiencing climate-induced home damage increases the odds of moving up to 1 kilometre within a year by 6.9 percentage points, compared to just 1.6 percentage points for moves of up to 25 kilometres. This finding has important implications for future research. Most datasets, including censuses, do not provide distance-based measures of population movement and define internal migration as a change of administrative unit, often using first-tier units, such as states (Thiede, Gray, and Mueller 2016), and second-tier units, such as counties (Fussell, Curtis, and DeWaard 2014). As our results show, most climate-induced moves will be missed in studies relying on coarse geographies which are commonly used in climate-induced mobility research (Hoffmann et al. 2023). In the absence of distance-based measure of population movement, future studies should endeavour to draw on lower-level spatial units that ideally correspond to the suburb level or below to capture the full scale of climate-induced population movement. The fact that most moves occur over short distances raises questions about whether displaced residents will be exposed to similar natural hazards in the future. This observation deserves further attention, given the recurrency of floods and cyclones within certain areas of Australia. For example, the city of Lismore in Northern New South Wales recoded 138 floods in the past 152 years, including 26 major floods (Morrison 2023; Callaghan and Power 2014).

Second, the impact of sudden-onset climate-events on home damage is highly inequitable and follows a clear socio-economic gradient. Tertiary-educated individuals are significantly less likely to experience disaster-induced home damage, which may be the result of greater access to, or use of, information about at-risk locations or greater knowledge about home-resilient design features and funding opportunities. Duration of residence also plays a role, with individuals residing in the same area for a decade or more reporting a lower likelihood of sustaining climate-induced home damage. This may be due to a lack of knowledge about low-lying areas among newcomers, to housing enhancements by long-term residents (e.g., better water insulation or bushfire preparedness), or to a progressively tighter housing market that increasingly places a cost premium on safe areas. Importantly, low-income earners are more likely to experience climate-induced home damage and more likely to be displaced than high-income earners. This may occur due to a concentration of low-income households in low-lying or wildfire-prone areas, an increased likelihood to sustain home damage due to poor quality housing, and/or fewer resources for recovery in place—as observed in New Orleans following Hurricane Katrina (Fussell et al. 2010). Australian evidence is limited, but what is available does suggest that disadvantaged communities are more likely to be exposed to both floods (Rolfe et al. 2020) and bushfires (Akter and Grafton 2021). Thus, more work, is required to understand the root causes of vulnerability in the Australian context and to identify the social and economic factors that contribute to the creation and exacerbation of risk to natural hazards among the most disadvantaged groups (Tierney 2020; Rhodes and Besbris 2022b).

The higher risk of disaster-induced mobility among disadvantaged groups runs counter to evidence for less developed countries, where the poorest are often trapped in place because of the lack of resources to move (Ayeb-Karlsson, Baldwin, and Kniveton 2022). Instead, we found that in Australia the poorest 3% account for 14% of the displaced population and the bottom half of the income distribution includes 80% of the population displaced by sudden-onset events. This contrast underscores the importance of considering heterogeneity in the drivers and consequences of climate-induced mobility in different macro-level contexts. In addition, our findings for Australia have important implications for climate-event responses, including the relevance of means-tested recovery funding. This approach to disaster recovery is currently not the norm within Australia, despite growing recognition that internally displaced Australians need more tailored support (Mortimer, Egbelakin, and Sher 2023).

Third, our findings for Australia revealed one factor that increases the risk of entrapment after climate-inducted home damage, namely a lack of home insurance among homeowners. Indeed, uninsured homeowners were the only group of those considered that exhibited a decrease in the likelihood of moving after climate-inducted home damage. This is a concerning finding, particularly given forecasts of 1 in 25 dwellings in Australia being uninsurable by 2030 (CCA 2023). Our results therefore suggest that a growing share of the current and future Australian population may be trapped in place because of uninsurance and unable to move after sustaining climate-induced home damage. Indeed, evidence from the United States has shown that disasters increase inequalities, as wealthier individuals and communities are better equipped to recover and rebuild their homes than lower-income populations who face greater challenges and longer recovery times (Rhodes and Besbris 2022b). Our findings call for a deeper understanding of the impact of insurance coverage and government-funded post-disaster schemes on mobility in the Australian context.

Fourth, residential mobility is currently not a common household strategy in response to climate-inducted home damage in Australia. Indeed, our results reveal that most people who sustain such damage remain immobile. Based on a robust and rigorous PSM methodology, we estimate that approximately 22,000 people aged 15 and over were displaced each year from 2009 to 2022—a period characterised by unusually catastrophic and recurrent flooding and wildfires. Importantly, this estimate is substantially lower than what could be concluded by simply glancing at the descriptive statistics. Based on the latter, we would have concluded that 20% of individuals who sustained climate-induced home damage would have moved houses by the following year. This serves as a reminder of the importance of stringent methodological choices—in this case PSM over traditional descriptive and regression methods—to derive reliable and realistic estimates of climate-induced residential mobility. Given the ongoing debate about the selection of matching techniques and increasing reliance of Coarsened Exact Matching (King and Nielsen 2019), future studies on disaster-induced mobility could explore the sensitivity of results to the choice of matching technique—something that has been rarely done in disaster-mobility literature.

While our estimate is nationally representative, only a few communities are affected by extreme weather events every year and, as a result, the impact of displacement is likely to be felt more strongly in some localities. More importantly, climate-induced home damage exerts a significant and long-lasting impact on the subjective well-being of affected individuals (Gunby and Coupé 2023). Yet it remains unclear whether those displaced due to climate hazards have better outcomes than those trapped in place. These are issues that warrant further investigation.

While our estimates of climate-induced mobility represent just a small fraction of overall population movement in Australia, they revealed that the average impact of climate-induced home damage on the odds of moving is comparable in magnitude to the impact of more-widely-researched life-course events such as marital separation and childbirth, but significantly greater than loss of employment, marriage and retirement. However, it is important to remember that our focus is only on the direct impact of housing sudden-onset climate events operating through home damage. The full impact of climate change on residential mobility will be larger when considering the indirect impacts caused by other factors, such as infrastructure damage, increased risk perceptions, and changes in livelihood (Black et al. 2011). These are empirically captured in most models by determining whether an individual lived in a neighbourhood, city or county that was affected by a specific extreme weather event. The data at hand did not enable us to assess exposure to extreme weather events (without ensuing home damage. Future work could combine the housing-damage question used in this paper with external data on exposure to extreme-weather events. This would help quantify and disentangle the direct and indirect impacts of extreme weather events on residential mobility.

In reflecting on the implications of our findings, it is important to also acknowledge the limitations of this study. First, analyses of the HILDA Survey were restricted by small cell sizes, which prevented us from calculating year-, state- or region-specific estimates. An alternative data source for future research is the Personal Level Integrated Data Asset (PLIDA), a novel administrative longitudinal micro dataset that provides geographically detailed information on place of residence based on the triangulation of multiple administrative datasets (Bernard et al. 2024; ABS 2024). These new data could potentially be deployed to identify place-based attributes that interact with climate-induced mobility once the reliability of its geo-spatial attributes has been fully assessed. Such dataset could also help us better understand the temporal dynamics of disaster-induced mobility. Our results tentatively suggests that as many as 40% of residents who moved because of climate-induced home damage were still living elsewhere three years on. By leveraging the full population count offered by PLIDA, future research ought to explore these dynamics in more depth, including spatio-temporal variations in exposure to extreme weather events at smaller scales.

Second, the HILDA Survey does not provide information on the hazard type experienced by respondents as the question on home damage was asked jointly for floods, cyclones and bushfires. This impairs our ability to recognise whether and how climate risks may be shaped by the nature of specific climatic hazards, as posited by the exposure-hazard-vulnerability framework (McLeman et al. 2021). Also missing from the HILDA Survey is information on the scale of climate-induced home damage, which would be required to identify possible thresholds in the impact of sudden-onset climate events on population movement (McLeman 2018). The available measure only enabled us to estimate the impact of the average home damage on residential mobility. As new data become available, these aspects represent opportunities for future refinement of the findings presented here.

Notwithstanding these limitations, the present study has provided a first causal estimate of climate-induced residential mobility in Australia, where research on the disaster-mobility nexus remains in its infancy. Our findings confirmed the importance of considering how wider societal contexts help drive climate mobility and the need to broaden the evidence base to high-income countries such as Australia, which are increasingly vulnerable to extreme weather events. Given that climate change is expected to intensify in tandem with rapid national population growth (OECD 2024), more research is urgently needed to fully understand the impacts of climate-induced mobility on both individuals and communities. Among others, policy interventions should attempt to limit exposure amongst those most impacted, such as low-income residents and uninsured homeowners. In light of our findings, failing to do so will likely result in a growing divide between the rich and the poor, contributing to the exacerbation of existing socio-economic inequalities within the country (Hérault et al. 2024; Sila and Dugain 2019).

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Online Supplementary Materials

Appendix A Descriptive statistics, unweighted sample

	Percentage
Home damage caused by an extreme weather event	1.33
Changed address	16.00
Socio-demographic characteristics	
Age	
15-24 years	18.24
25-44 years	34.04
45-64 years	30.62
65+ years	17.10
Gender	
Male	47.25
Female	52.75
Marital status	
Married or partnered	63.17
Divorced or separated	13.40
Never married	23.43
Has dependent children	65.73
Foreign-born	20.82
Housing tenure	
Insured homeowner	2.07
Uninsured homeowner	65.85
Renter	32.08
Socio-economic status	
Tertiary educated	25.42
Self-reported financial prosperity	
Very poor	0.77
Poor	2.64
Just getting along	25.50
Reasonably comfortable	52.27
Very comfortable	18.82
Income quartile	
Lowest quartile	25.00
Medium low	25.00
Medium high	25.00
Highest quartile	25.00
Duration of residence	
Less than a year	15.84
1 to 4 years	29.36
5 to 9 years	17.20
10+ years	34.75
Insufficient information	2.85
Locational characteristics	
Non- metropolitan area	38.30
State/Territory of residence	
New South Wales	29.55
Victoria	25.24
Queensland	21.21
South Australia	9.04

	Western Australia	8.95
	Tasmania	3.22
	Northern Territory	0.74
	Australian Capital Territory	2.05
Survey year		
	2009	5.68
	2010	5.77
	2011	7.52
	2012	7.46
	2013	7.47
	2014	7.47
	2015	7.52
	2016	7.55
	2017	7.5
	2018	7.44
	2019	7.45
	2020	7.29
	2021	7.06
	2022	6.81

Notes: HILDA Survey, 2009-2022.

Appendix B Standardised difference and variance ratio for the raw and matched samples

Two key statistical measures for PSM balance assessment are the standardised mean difference between the treatment and control groups and the treated-to-control variance ratio. Both are reported in Table B1 for the raw and matched samples in our main analyses. A perfectly balanced covariate has a standardised difference of zero and variance ratio of one. This ideal-typical situation is however very rare. Rather, there is agreement in the literature that good balance is denoted by a standardised mean difference ranging from –0.25 to 0.25, and a variance ratio between 0.5 and 2 (Stuart and Ialongo 2010). However, some authors have set a smaller threshold of 0.1 for the standardised mean difference (Nguyen et al. 2017).

Results in Table B1 provide strong evidence of a good balance in our matched sample, as shown by standardised differences close to zero and variance ratios of around one. Importantly, the standardised differences—which are key to reduced bias—are below 0.10 for all covariates in the matched sample. The improvement is particularly visible for housing tenure, educational attainment, non-metropolitan settlement and most year fixed effects. These results are visualised in Figure C1, which displays the probability density function of the propensity scores for the treated and controlled groups in the raw and matched samples. All in all, the distribution of the propensity scores confirms a good balance in the matched sample.

The category representing missing information on duration of residence has a small standardised difference, but a large variance ratio in the matched sample. This is, however, not a source of concern, as this variable is not related to exposure to climate-induced home damage. Reassuringly, all location variables exhibit standardised differences close to zero in our matched sample. However, the variance ratio is large (yet below 2) for Tasmania and the Northern Territory. This indicates dispersed values for those cells. This pattern of results reflects the unbalanced distribution of the Australian population, with 75% of it concentrated on the eastern seaboard of New South Wales, Victoria and Queensland.

Table B1 Standardised differences and variance ratios between the treated and control groups for the raw and matched samples

	Standardised difference		Variance ratio	
	Raw	Matched	Raw	Matched
Socio-demographic characteristics				
Age				
14-24 years	-0.04	-0.03	0.93	0.95
25-44 years	0.02	-0.02	1.02	0.98
45-64 years	0.05	0.03	1.03	1.02
65+ years	-0.05	0.02	0.91	1.03
Sex	0.02	-0.01	1.00	1.00
Marital status				
Married or partnered	0.04	0.05	0.97	0.96
Divorced or separated	0.01	-0.01	1.02	0.98
Never married	-0.05	-0.05	0.93	0.93
Dependent children	0.09	0.04	0.93	0.97
Foreign-born	0.08	-0.02	0.89	1.02
Housing tenure				
Uninsured homeowner	0.06	0.00	1.50	1.03
Insured homeowner	-0.04	0.01	1.03	0.99
Renter	0.02	-0.01	1.02	0.99
Socio-economic status				
Income quartile				
Bottom	0.01	-0.01	1.01	0.99
Middle bottom	0.04	0.02	1.04	1.02
Middle top	-0.02	0.01	0.98	1.01
Top	-0.03	-0.02	0.96	0.98
Tertiary education	-0.20	-0.02	0.88	0.98
Duration of residence				
Less than 1 a year	0.05	-0.01	1.09	0.99
1 to 4 years	0.05	0.02	1.05	1.02
5 to 9 years	0.00	0.01	1.00	1.02
10+ years	-0.08	-0.02	0.95	0.99
Insufficient information	-0.01	-0.04	0.82	0.54
Locational characteristics				
Non-metropolitan	0.29	0.08	1.06	1.03
State and territory				
New South Wales	0.11	0.01	1.09	1.01
Victoria	-0.21	0.02	0.74	1.02
Queensland	0.29	-0.04	1.35	0.94
South Australia	-0.23	-0.06	0.42	0.83
Western Australia	-0.12	0.02	0.68	1.05
Tasmania	-0.05	0.06	0.74	1.32
Northern Territory	0.04	0.04	1.55	1.52
Australian Capital Territory	-0.03	0.01	0.79	1.07
Year				
2009	-0.04	-0.03	0.85	0.90
2010	0.01	0.06	1.03	1.25
2011	0.20	-0.05	1.88	0.82
2012	-0.04	0.00	0.89	0.99
2013	-0.07	-0.06	0.79	0.82
2014	-0.21	0.01	0.41	1.03
2015	0.01	-0.01	1.04	0.96
2016	-0.10	0.04	0.70	1.12
2017	-0.03	0.03	0.90	1.09
2018	-0.13	0.02	0.62	1.06
2019	-0.06	-0.01	0.83	0.97
2020	-0.05	0.03	0.85	1.08
2021	-0.07	-0.01	0.79	0.98
2022	0.38	-0.04	2.43	0.88

Notes: HILDA Survey, 2009-2022.

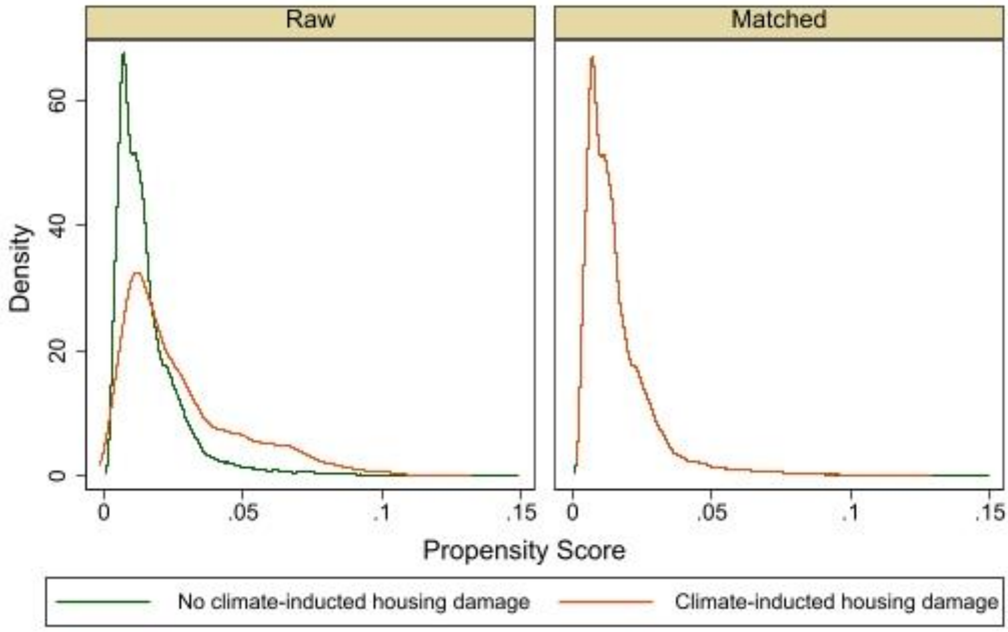


Figure B1 Density function of the propensity scores for the treated and control groups in the raw and matched samples

Notes: HILDA Survey, 2009-2022.

Appendix C Logistic regression model of extreme-weather-related home damage with self-reported socio-economic status

	Odds ratio	Standard errors	Predicted probability	95% confidence interval	
Socio-demographic characteristics					
Age (ref. cat. 15-24 years)			1.74	1.51	1.97
25-44 years	0.95	[0.82,1.10]	1.65	1.53	1.78
45-64 years	0.95	[0.80,1.12]	1.66	1.53	1.79
65+ years	0.79*	[0.65,0.96]	1.38	1.22	1.55
Sex (ref. cat. Male)			1.65	1.55	1.75
Female	0.96	[0.89,1.04]	1.59	1.50	1.68
Marital status (ref. cat. Married or partnered)			1.66	1.56	1.76
Divorced or separated	0.94	[0.82,1.08]	1.57	1.38	1.76
Never married	0.90	[0.78,1.04]	1.50	1.31	1.68
Dependent children (ref. cat. No)			1.49	1.35	1.63
Yes	1.13*	[1.00,1.29]	1.67	1.57	1.78
Foreign-born (ref. cat. No)			1.64	1.56	1.72
Yes	0.92	[0.82,1.04]	1.52	1.35	1.67
Housing tenure (ref. cat. Insured homeowner)			1.69	1.59	1.79
Uninsured homeowner	1.60***	[1.17,2.19]	2.28	1.61	2.99
Renter	1.18**	[1.06,1.31]	1.44	1.32	1.56
Socio-economic status					
Self-reported financial prosperity (ref. cat. very poor]			3.63	2.61	4.66
Poor	0.86	[0.61,1.20]	3.14	2.57	3.71
Just getting along	0.53***	[0.39,0.71]	1.96	1.81	2.12
Reasonably comfortable	0.38***	[0.28,0.52]	1.45	1.36	1.53
Very comfortable	0.34***	[0.25,0.47]	1.29	1.12	1.43
Educational attainment (ref. cat. no tertiary education)			1.65	1.56	1.73
Tertiary education	0.91	[0.83,1.07]	1.50	1.36	1.66
Duration of residence (ref. cat. less than 1 year)			1.78	1.60	1.96
1 to 4 years	0.95	[0.84,1.07]	1.68	1.56	1.81
5 to 9 years	0.86*	[0.74,0.99]	1.54	1.38	1.70
10+ years	0.87*	[0.74,0.98]	1.52	1.40	1.65
Insufficient information	0.75	[0.44,1.28]	1.34	0.65	2.03
Locational characteristics					
Urban status (ref. cat. Metropolitan)			1.30	1.21	1.39
Non-metropolitan	1.61***	[1.47,1.78]	2.07	1.94	2.26
State/Territory (ref. cat. Victoria)			1.11	0.98	1.25
New South Wales	1.78***	[1.53,2.05]	1.97	1.81	2.12
Queensland	2.14***	[1.85,2.47]	2.35	2.16	2.54
South Australia	0.59***	[0.46,0.75]	0.66	0.52	0.81
Western Australia	0.99	[0.79,1.22]	1.11	0.91	1.31
Tasmania	0.79	[0.58,1.09]	0.89	0.64	1.12
Northern Territory	1.91***	[1.24,2.95]	2.12	1.26	2.97
Australian Capital Territory	1.50*	[1.04,2.17]	1.67	1.10	2.22
Number of observations			192,780		
Number of individuals			23,552		
Log likelihood			-14,969		

Notes: HILDA Survey, 2009-2022. The model controls also for survey year (parameters not shown). Statistical significance: *** p<0.001; ** p<0.01; * p<0.05.

Appendix D Percentage of the total and displaced populations, by socio-economic status

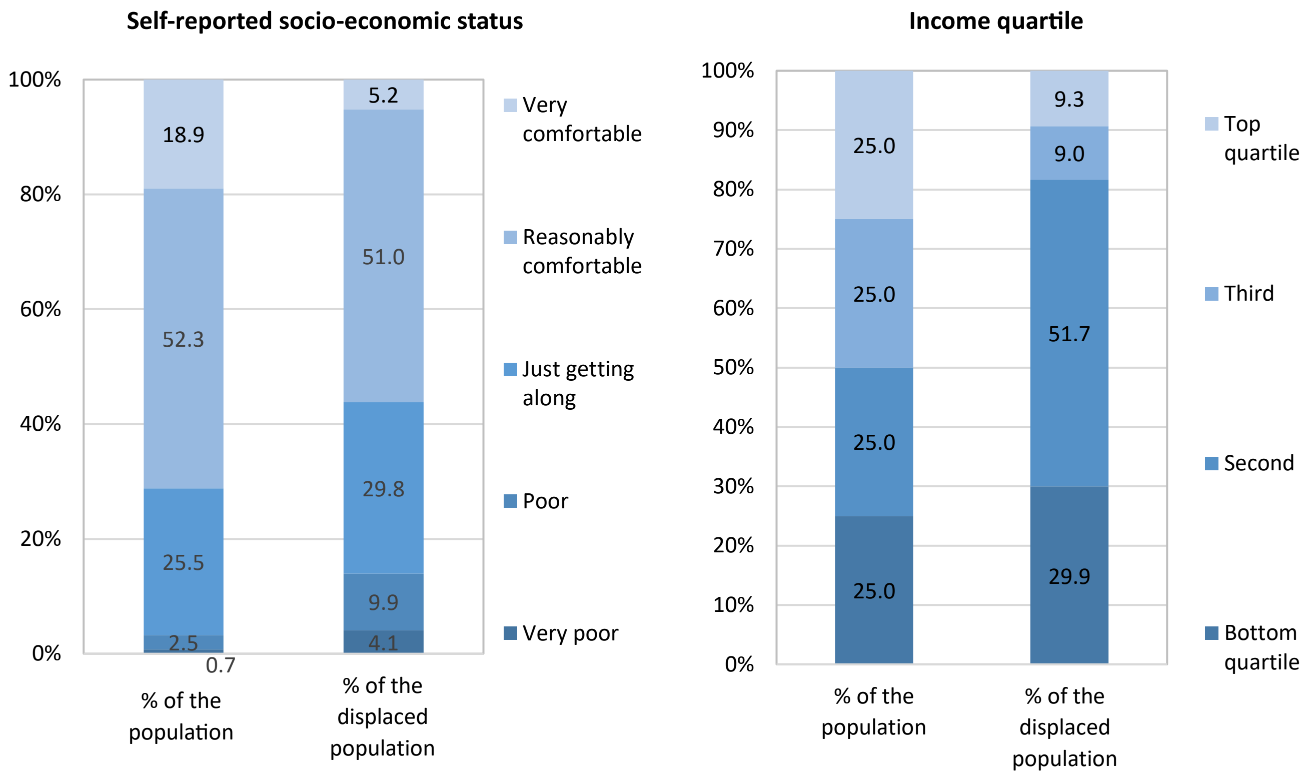


Figure D1. Percentage of the total and displaced populations, by socio-economic status
Notes: HILDA Survey, 2009-2022. Calculations based on information in Figure 6 and Appendix A.

Table 1 Balance and sample size for the raw sample and the data used by selected matching techniques

	Balance	Sample size
	Average of the absolute standardised mean difference across all covariates (MASD)	Number of observations matched
Raw sample	0.087	3,111
His Mahalanobis distance nearest neighbour matching	0.074	3,111
Mahalanobis distance kernel matching	0.071	3,018
One-to-one propensity score matching	0.023	3,111
Coarsened exact matching	0.000	2,309

Notes: $MASD = \frac{1}{K}\sum_{k=1}^{K}|SMD_k|$, where K is the number of covariates. $SMD = \bar{X}_T - \bar{X}_C \Big/ \sqrt{(S_T^2 + S_C^2)/_2}$, where $\bar{X}_T$ and $\bar{X}_c$ are the means of the covariates for the treated and the control group respectively and S_T and S_C are the standard deviations. Lower MASD values denote better balance between the treated and the control group. Higher sample sizes denote fewer observations being lost in the matching.

Table 2 Logistic regression model of extreme-weather-related home damage, main results

	Odds ratio	Standard errors	Predicted probability	95% confidence interval	
Socio-demographic characteristics					
Age (ref. cat. 15-24)			1.67	1.45	1.91
25-44 years	1.01	[0.87,1.17]	1.69	1.56	1.83
45-64 years	1.01	[0.85,1.20]	1.69	1.56	1.82
65+ years	0.79*	[0.63,0.96]	1.13	1.14	1.48
Sex (ref. cat. Male)			1.65	1.55	1.75
Female	0.96	[0.89,1.04]	1.59	1.49	1.67
Marital status (ref. cat. Married or partnered)			1.64	1.54	1.73
Divorced or separated	0.99	[0.86,1.15]	1.63	1.42	1.83
Never married	0.94	[0.81,1.10]	1.54	1.35	1.73
Dependent children (ref. cat. No)			1.45	1.231	1.58
Yes	1.18*	[1.04,1.34]	1.70	1.59	1.80
Foreign-born (ref. cat. No)			1.64	1.55	1.72
Yes	0.93	[0.82,1.05]	1.52	1.36	1.69
Housing tenure (ref. cat. Insured homeowner)			1.63	1.54	1.73
Uninsured homeowner	1.57***	[1.15,2.14]	2.37	1.67	3.06
Renter	1.07	[0.96,1.19]	1.53	1.40	1.66
Socio-economic status					
Income quartile (ref. cat. Lowest quartile)			1.52	1.51	1.87
Second quartile	0.98	[0.85,1.11]	1.51	1.51	1.79
Third quartile	0.92	[0.79,1.07]	1.42	1.42	1.71
Highest quartile	0.92	[0.79,1.09]	1.41	1.41	1.71
Educational attainment (ref. cat. no tertiary education)			1.67	1.59	1.76
Tertiary education	0.85***	[0.76,0.96]	1.43	1.39	1.57
Duration of residence (ref. cat. less than 1 year)			1.77	1.59	1.96
1 to 4 years	0.96	[0.85,1.08]	1.70	1.57	1.82
5 to 9 years	0.87	[0.75,1.01]	1.55	1.39	1.71
10+ years	0.85*	[0.74,0.98]	1.51	1.38	1.63
Insufficient information	0.74	[0.43,1.26]	1.32	0.06	1.99
Locational characteristics					
Urban status (ref. cat. Metropolitan)			1.30	1.21	1.38
Non-metropolitan	1.63****	[1.47,1.80]	2.08	1.94	2.22
State/Territory (ref. cat. Victoria)			1.11	0.98	1.25
New South Wales	1.77***	[1.53,2.05]	1.96	1.80	2.11
Queensland	2.16***	[1.87,2.50]	2.38	2.19	2.56
South Australia	0.59***	[0.46,0.75]	0.66	0.52	0.80
Western Australia	1.00	[0.81,1.24]	1.12	0.92	1.31
Tasmania	0.79	[0.57,1.08]	0.89	0.63	1.11
Northern Territory	1.83***	[1.19,2.82]	2.02	1.21	2.83
Australian Capital Territory	1.45	[0.99,2.10]	1.61	1.05	2.16
Number of observations			192,780		
Number of individuals			23,522		
Log likelihood			-15,131		

Notes: HILDA Survey, 2009-2022. The model controls also for survey year (parameters not shown). Statistical significance: *** p<0.001; ** p<0.01; * p<0.05.

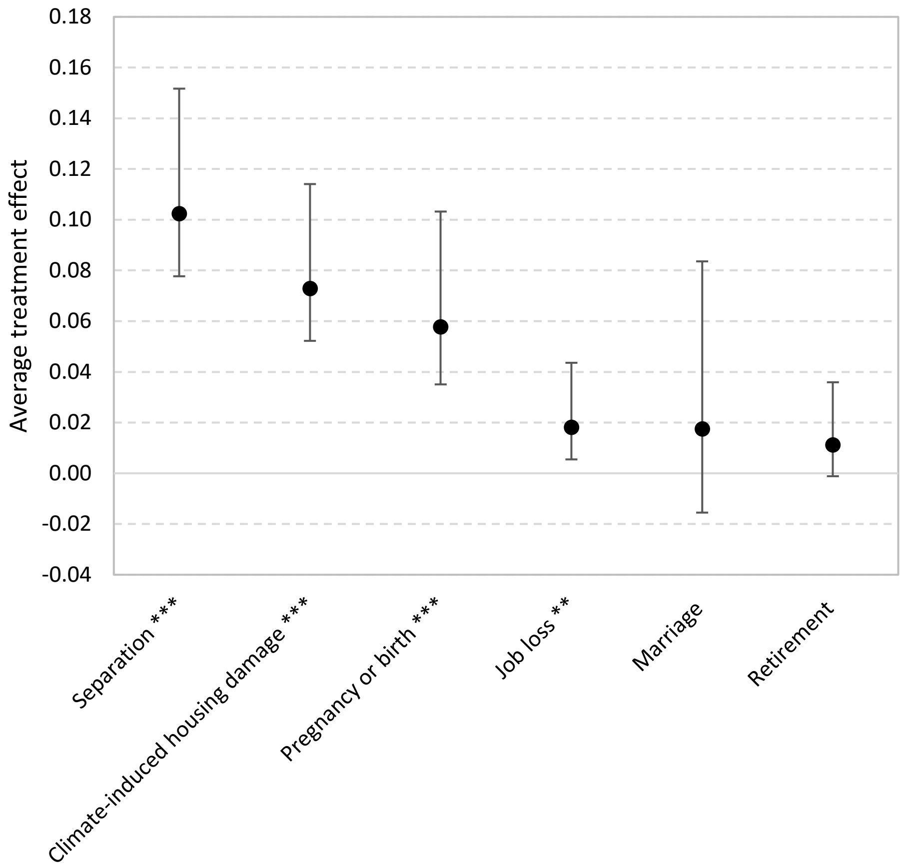
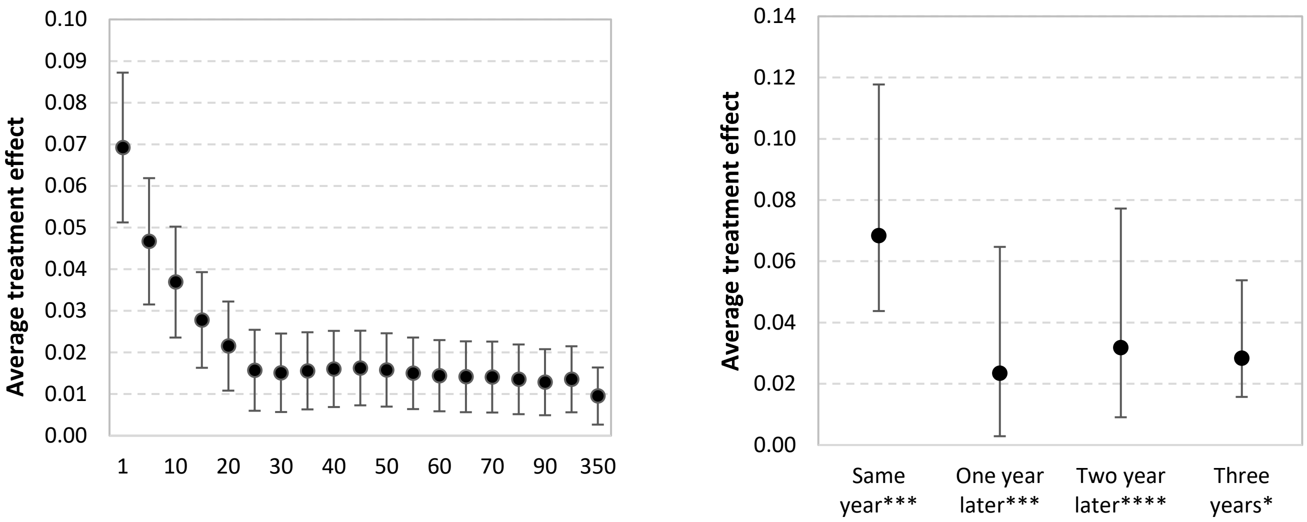


Figure 1 Average treatment effect with 95% confidence interval by life-course event

Notes: HILDA Survey, 2009-2022. The average treatment effect is the average difference in percentage points in residential mobility between the treated (i.e., individuals who experienced home damaged caused by extreme weather events) and the untreated (i.e., individuals with no such experience) after balancing the covariates between the two groups. Statistical significance: *** p<0.001; ** p<0.01; * p<0.05.

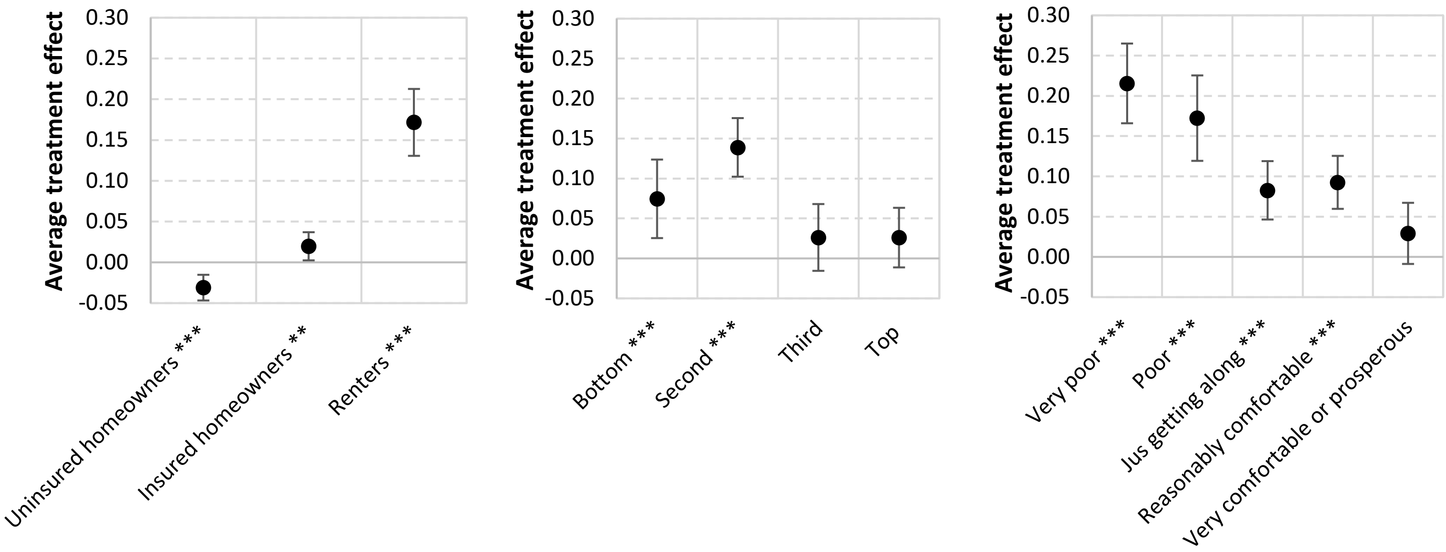


2a. Maximum distance moved (kilometres)

2b. Time since disaster-induced housing damage occured

Figure 2 Average treatment effect with 95% confidence interval by distance moved and time since disaster

Notes: HILDA Survey, 2009-2022. The average treatment effect is the average difference in percentage points in residential mobility between the treated (i.e., individuals who experienced home damaged caused by extreme weather events) and the untreated (i.e., individuals with no such experience) after balancing the covariates between the two groups. All ATEs are statistically significant (p<0.05) for 2a. Statistical significance for 2b: *** p<0.001; ** p<0.01; * p<0.05.



3a. Home tenure **3b. Income quartile** **3c. Self-reported socio-economic status**

Figure 3 Average treatment effect with 95% confidence interval by housing tenure and socio-economic status

Notes: HILDA Survey, 2009-2022. The average treatment effect is the average difference in percentage points in residential mobility between the treated (i.e., individuals who experienced home damaged caused by extreme weather events) and the untreated (i.e., individuals with no such experience) after balancing the covariates between the two groups. Statistical significance: *** p<0.001; ** p<0.01; * p<0.05.

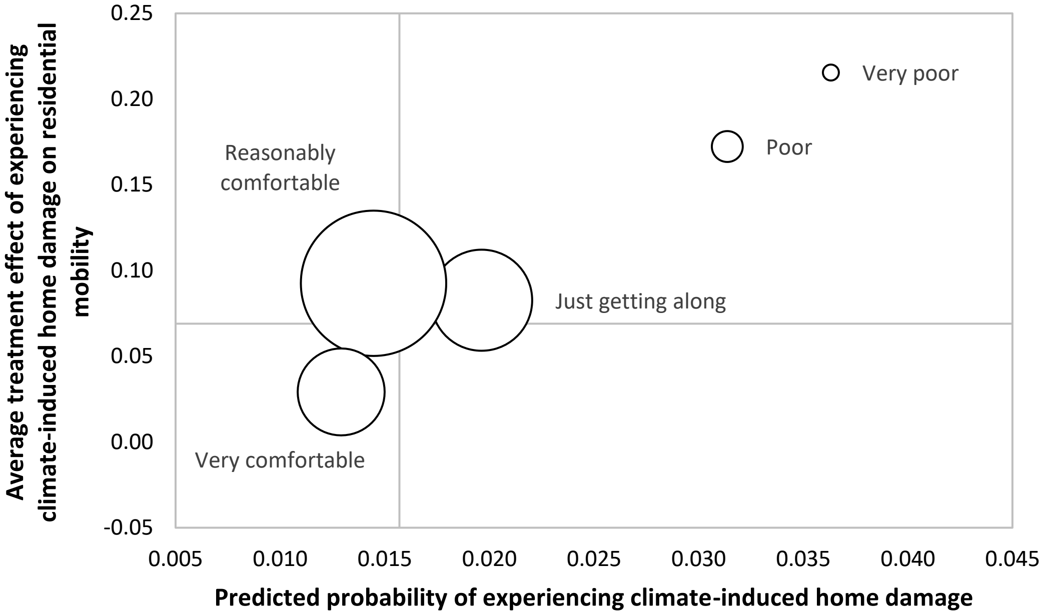


Figure 4 Risk of exposure against risk of displacement by self-reported socio-economic status

Notes: HILDA Survey, 2009-2022. The predicted probability of experiencing climate-induced home damage is obtained from the regression model in Appendix E. The ATE is obtained from Figure 2b. The bubbles represent the size of each group in the population, as reported in Appendix A.