Nguyen, Ha Trong; Mitrou, Francis

Working Paper

Residential responses to cyclones: New evidence from Australia

GLO Discussion Paper, No. 1426

Provided in Cooperation with:
Global Labor Organization (GLO)

Residential responses to cyclones: New evidence from Australia

Ha Trong Nguyen[*, †] Francis Mitrou[†]

By leveraging randomly timed exposure to local cyclones as natural experiments, this study pioneers a comprehensive causal analysis of cyclone impacts on residential outcomes among Australian individuals. Drawing upon over two decades of nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia survey, coupled with historical cyclone records, individual fixed effects models uncover substantial increases in reported home damage. Planned relocation intentions and actual migration experiences show moderate increases, particularly in cases of higher cyclone severity and proximity. Additionally, these cyclones prompt individuals to acknowledge the significance of home-related insurance and actively seek coverage. Alongside long-distance domestic migration, insurance acquisition emerges as another alternative coping mechanism, effectively mitigating future repair costs. Extensive heterogeneity analyses reveal that the choice among these coping strategies depends on factors such as cyclone severity, age, prior homeownership, income, insurance coverage, rural/urban residence, coastal proximity, and community cyclone history. Moreover, the study identifies home damage from cyclones as a key factor driving observed migration patterns.

Keywords: Natural Disasters; Migration; Insurance; Australia

JEL classifications: G22; G52; J61; Q54; R23

---

[*] **Corresponding author**: Telethon Kids Institute | Tel: +61 8 6319 1019 | Postal: GPO Box 855, Perth WA 6872, Australia | Email: ha.nguyen@telethonkids.org.au.

[†] Telethon Kids Institute & The University of Western Australia & Global Labor Organization

Acknowledgements: We are grateful to Nicole Black, Ana Gamarra, Jan Kabátek, Danusha Jayawardana, Kristin Kleinjans, David Johnston, Steeve Marchand, John de New, Anthony Scott, Diana Suarez, Dennis Petrie, Anh Trinh, Federico Zilio, and seminar participants at Monash University and The University of Melbourne for helpful comments and feedback. This research was partly funded by the Australian Research Council Centre of Excellence for Children and Families over the Life Course (#CE200100025). This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

1. Introduction

Climate change is significantly impacting societies worldwide, with natural disasters like cyclones/hurricanes/typhoons[1] posing a growing threat (Elsner *et al.* 2008; Dell *et al.* 2014; Carleton & Hsiang 2016). Extensive research explores the social and economic consequences of these events, with a particular focus on the link between natural disasters and migration patterns (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020). Acknowledging the distinct nature and impacts of different disasters, a growing body of research investigates the specific relationship between cyclones and migration (Gröger & Zylberberg 2016; Sheldon & Zhan 2022).

While much of this research focuses on developing countries, where cyclones can trigger both domestic and international migration (Mahajan & Yang 2020; Chort & de la Rupelle 2022), studies on developed nations remain scarce. Existing research in developed countries, primarily the US, examines the domestic migration effects of cyclones using aggregate data or cross-sectional individual-level data (Smith *et al.* 2006; McIntosh 2008; Sheldon & Zhan 2022). However, these data limitations, which are also common among studies focusing on developing countries, prevent them from controlling for individual time-invariant factors, including residential preferences, which may be correlated with both cyclone exposure and migration decisions (Dell *et al.* 2014). Additionally, akin to numerous other studies focusing on the broader relationship between natural disasters and migration, these studies are constrained by data that do not permit an exploration of alternative coping mechanisms alongside migration (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020). Furthermore, existing evidence does not

[1] Because this study focuses on Australia, we use a regional specific name for this weather event as a "tropical cyclone" or "cyclone", alternatively. In the Australian region, a tropical cyclone is defined as a warm-cored, non-frontal low-pressure system of synoptic scale developing over warm waters. It features organized convection and a 10-minute mean wind speed exceeding 63 km/h that extends more than halfway around the centre and persists for at least 6 hours (Bureau of Meteorology (BOM), 2024). Other regional specific names for a cyclone include "hurricane" (Currie & Rossin-Slater 2013; Mahajan & Yang 2020; Sheldon & Zhan 2022) and "typhoon" (Gröger & Zylberberg 2016; Franklin & Labonne 2019).

fully elucidate the factors motivating individuals affected by natural disasters in developed countries to relocate.

Australia, a developed nation demonstrably susceptible to cyclones, has experienced a notable lack of research concerning the ramifications of these events on residential choices (Hickson & Marshan 2022; Johar *et al.* 2022). This dearth of knowledge presents a unique opportunity to contribute meaningfully to the existing body of research. By leveraging over two decades of nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, this study delves into the residential responses triggered by cyclones. The investigation yields four key contributions to the literature.

First, this study pioneers a comprehensive analysis of cyclone impacts on residential outcomes among Australians. By analysing the impacts of cyclone exposure on various residential outcomes, including home damage, relocation intentions, actual migration patterns, and home-related insurance uptake, our research provides critical evidence on how Australians respond to these typically devastating events. Understanding these responses is crucial for developing effective policies to mitigate the social and economic consequences of cyclones not only for Australia but also for other natural disaster-prone countries (Black *et al.* 2011; Carleton & Hsiang 2016).

Second, our study benefits from the utilisation of unique and high-quality datasets, enabling substantial methodological and empirical progress. Specifically, the utilisation of a comprehensive longitudinal individual dataset tracking individuals who relocate affords us the opportunity to employ an individual Fixed-Effects (FE) model. This method effectively controls for unobservable individual time-invariant factors, allowing for the quantification of cyclone effects on migration for the first time. By employing this robust model, we address a prevailing concern within the existing literature regarding the potential confounding influence of such factors on estimation accuracy (Dell *et al.* 2014). Additionally, we refine our identification strategy by applying this individual FE model to quantify the causal impacts of different cyclone exposure measures which are exogenously determined by the distance from the individual's residing postcode centroid to the cyclone's eye and the cyclone category.

Moreover, the abundance of data provided by our extensive survey dataset, in conjunction with historical cyclone records documenting over 80 cyclones that made landfall during the survey period, empowers us to conduct an exceptionally thorough heterogeneous analysis (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020). Specifically, we can explore the differential responses to cyclones of varying severity across diverse sub-populations, as identified by gender, age, prior homeownership, income, insurance coverage, rural/urban residence, coastal proximity, and community cyclone history. This extensive heterogeneous analysis sheds light on the channels through which cyclones affect residential choices and other potential coping mechanisms. It also helps identify vulnerable groups and regions for targeted support and resilience-building strategies (Cattaneo *et al.* 2019).

Third, this is the first study to explore alternative coping mechanisms alongside migration. Previous studies primarily focus on the relationship between natural disasters and migration (Cattaneo *et al.* 2019; Kousky 2019; Kaczan & Orgill-Meyer 2020). This study goes further by identifying home-related insurance acquisition as another alternative coping mechanism that emerges alongside migration. Our extensive heterogeneous analyses reveal that these two coping mechanisms are employed very differently, depending on cyclone severity and various individual, household, and locality characteristics. This contribution is particularly important given the substantial gaps in the literature regarding adaptation strategies and their interactions (Black *et al.* 2011; Carleton & Hsiang 2016).

Fourth, this study is the first to explore the factors influencing cyclone-induced migration, providing a deeper understanding of the channels through which natural disasters influence residential choices and the interplay between various potential coping mechanisms.

By exploiting the natural experiment of randomly timed exposure to local cyclones affecting the same individuals over time, this study yields four main findings. First, our results demonstrate that cyclones, particularly those of greater severity and closer proximity to homes, significantly increase reported home damage. Additionally, cyclones moderately amplify intentions for relocation and actual migration patterns. Notably, the findings reveal that cyclones primarily drive long-distance domestic migration.

Second, we reveal that, alongside long-distance domestic migration, acquiring home-related insurance emerges as another significant coping mechanism. Our findings strongly suggest that individuals are prompted to recognize the importance of insurance and actively seek coverage in response to cyclones, particularly those of greater intensity and proximity to homes, occurring in both the current and previous years. This strategy effectively alleviates much of the financial burden associated with future repair costs stemming from cyclone damage.

Third, our extensive heterogeneity analyses demonstrate that the utilisation of these two coping strategies varies based on cyclone severity and various individual, household, and locality characteristics. Specifically, in response to more severe cyclones, cyclone-affected individuals may choose either relocate or purchase (more) home-related insurance. Furthermore, the analysis reveals that individuals with specific characteristics, such as younger individuals, renters, wealthier individuals, those without existing insurance, and residents of rural areas, coastal areas, or historically cyclone-free regions, are more likely to migrate in response to experiencing a cyclone in their location. Conversely, individuals with contrasting characteristics, including males, younger individuals, homeowners, wealthier individuals, and residents of rural areas, inland areas, or historically cyclone-exposed regions, are more likely to purchase home insurance when affected by cyclones. Our further exploration into the dynamic effects of cyclones on residential outcomes reveals that, when facing less severe cyclones, individuals may choose to reinforce their existing homes, likely facilitated by claims from previously secured home-related insurance, to enhance future resilience. Fourth, this study presents novel evidence demonstrating that cyclone-induced home damage serves as a primary driver of observed migration patterns.

This paper proceeds as follows. Following a brief review of relevant literature in Section 2, Section 3 details our data and sample. The empirical model is presented in Section 4, with Section 5 showcasing the main results. Section 6 documents robustness checks, while Section 7 examines the heterogeneous effects of cyclones. We delve deeper into the relationship between cyclones and insurance behaviours in Section 8. Section 9 explores the dynamic impacts of cyclones on residential outcomes, followed by Section 10 which investigates the specific impact of home damage on residential choices. Finally, Section 11 concludes the paper.

2. Literature review

Our study significantly contributes to the vast body of research on the social and economic impacts of climate change (Dell *et al.* 2014; Carleton & Hsiang 2016). Within this extensive literature, our work aligns closely with research exploring the link between natural disasters and migration patterns (for reviews, see Cattaneo *et al.* (2019) or Kaczan and Orgill-Meyer (2020)). Studies in this area have examined the migration effects of various climatic factors, including temperature (Bohra-Mishra *et al.* 2014; Jessoe *et al.* 2018), rainfalls (Barrios *et al.* 2006), floods (Boustan *et al.* 2012) or dust storms (Hornbeck 2012).

Recognizing that the nature and impacts of natural disasters vary, a growing body of research specifically explores the relationship between cyclones and migration (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020).[2] The majority of these studies focus on developing countries,

[2] Our research also relates to studies on cyclone impacts on other outcomes such as economic growth (Hsiang & Jina 2014), income (Deryugina *et al.* 2018; Groen *et al.* 2020) and health (Currie & Rossin-Slater 2013; Bakkensen & Mendelsohn 2016).

examining either domestic migration (Gröger & Zylberberg 2016; Pajaron & Vasquez 2020) or international migration from these countries, primarily to the US (Spencer & Urquhart 2018; Mahajan & Yang 2020; Chort & de la Rupelle 2022).

Our study is most akin to a limited number of studies, exclusively from the US, that examine the domestic migration impacts of cyclones in a developed nation context. Notably, US research has explored the domestic migration effects of specific hurricanes like Hurricane Andrew (Smith *et al.* 2006) or Hurricane Katrina (McIntosh 2008), or the effects of multiple hurricanes (Ouattara & Strobl 2014; Fussell *et al.* 2017; Sheldon & Zhan 2022). Most US studies rely on aggregate data (e.g., county-level) with a few exceptions.[3] Notably, Smith *et al.* (2006) use data from two adjacent censuses, McIntosh (2008) utilises the Current Population Survey (CPS), and more recently, Sheldon and Zhan (2022) leverage the American Community Survey. However, the cross-sectional nature of these individual datasets necessitates spatial disaggregation (e.g., county-level) to quantify the migration effects of hurricanes. Our study stands out by being the first to leverage individual panel data from a developed nation context, specifically Australia.

Our research also relates to the increasing number of Australian studies exploring the socio-economic effects of extreme weather events. Existing Australian studies have utilised macro-level data to investigate the sectoral economic impacts of floods and bushfires (Ulubaşoğlu *et al.* 2019) or multiple natural disasters (Ladds *et al.* 2017). A limited number of other studies have employed individual-level data, primarily the HILDA dataset (also used in our study), to examine the effects of drought on life satisfaction (Carroll *et al.* 2009), floods and bushfires on income (Hickson & Marshan 2022), and the 2009 Black Saturday Bushfires on life satisfaction

[3] Studies investigating the relationship between cyclones and migration in developing countries predominantly rely on country-level (Spencer & Urquhart 2018; Mahajan & Yang 2020; Chort & de la Rupelle 2022), region-level (Pajaron & Vasquez 2020), or household-level (Gröger & Zylberberg 2016) data. Consequently, they are unable to control for individual fixed effects.

(Johnston *et al.* 2021) and trust (Magnusson & Roth 2023). More recent studies have utilised HILDA data to explore the effects of weather-related home damage on mental health (Baryshnikova & Pham 2019), economic outcomes (Johar *et al.* 2022) and life satisfaction (Gunby & Coupé 2023). However, none of these Australian studies have investigated the link between cyclones and residential outcomes, which is the focus of our work.

3. Data and sample

3.1. Data

Our study relies on two primary data sources. The first data source is from the Household, Income and Labour Dynamics in Australia (HILDA) survey. This nationally representative survey commenced in 2001, encompassing 7,682 households and more than 19,000 individuals. It systematically monitors individuals aged 15 years or older within private households on an annual basis, furnishing comprehensive individual and household-level data, encompassing residential particulars, health indicators, and labour market engagements (Summerfield *et al.* 2023). A key advantage is that HILDA follows individuals who relocate, maintaining the sample's representativeness and enabling us to analyse cyclone impacts on various outcomes, including residential choices, over time. We use the latest HILDA release, spanning 22 waves (2001-2022).

The second data source is a publicly available historical cyclone database obtained from the Australian Bureau of Meteorology (BOM). This database provides comprehensive information on all tropical cyclones south of the equator between latitudes 90E and 160E. For each recorded cyclone, it details the track (i.e., longitude, latitude, and time) and strength measures like wind speed and wind gust.[4]

[4] We were unable to use data on mean cyclone eye radius in our study due to extensive missing values for this item in the publicly available BOM data. See: http://www.bom.gov.au.

We connect the two datasets by matching the cyclone's path and timing from the historical cyclone database with the individual's residential postcode centroid and interview date from HILDA. We use the restricted HILDA version containing postcodes, as they offer the finest geographical granularity available.[5] As per the 2011 census, on average, each postcode contains roughly 8,500 people (across around 2,500 postcodes).

3.2. Cyclone exposure measures

To measure exposure to a cyclone, we first calculate the closest distance between the individual's postcode centroid and the cyclone's eye. The eye of a cyclone, a region of calm at the centre, is surrounded by the cyclone's strongest winds. Areas directly below the eye's path often experience the most severe damage (BOM 2024). A similar approach has been employed previously (Currie & Rossin-Slater 2013; Franklin & Labonne 2019; Groen *et al.* 2020; Deryugina & Marx 2021). While tropical cyclones in Australia typically sport an eye around 40 km wide (range: 10-100 km) (BOM 2024), we utilise three distance bands - 30 km, 60 km, and 100 km - to assess exposure and damage patterns across varying impact zones.

We additionally measure exposure to a cyclone by its category, ranging from 1 (weakest) to 5 (strongest). Particularly, we employ the BOM's suggested cutoffs to classify a cyclone basing on its maximum mean wind speed (BOM 2024). The respective maximum mean wind speed cutoff for each cyclone category is as follows (in km/h): Category 1 (≤88), 2 (>88 and ≤117),

[5] Australian studies have predominantly utilised data from the publicly available Australian Disaster Resilience Knowledge Hub (https://knowledge.aidr.org.au) to investigate the impacts of floods and bushfires (Ladds *et al.* 2017; Ulubaşoğlu *et al.* 2019; Hickson & Marshan 2022). However, we abstain from employing this database in our study for three primary reasons. Firstly, events included in this dataset are based on their actual damages, which are known to heavily depend on the socio-economic conditions in a region. These factors, including income and migration patterns, may confound the disaster estimates (Hsiang & Jina 2014; Guiteras *et al.* 2015). Secondly, less severe events are likely to be underrepresented in this database because events are included only if they induced a certain minimum level of damage (e.g., at least three deaths or at least $10 million in total estimated cost of damage). Thirdly, events in this database lack spatial detail, making it difficult to precisely capture their effects on individuals in our survey data. Specifically, disasters in this database are only available at the Statistical Area (SA) Level 4, which comprises only 108 SA4 regions in Australia. In contrast, our study utilises data from 2,500 postcodes. Our linked datasets address these data limitations. However, the finest geographical identifier available in the HILDA is the postcode, which lacks the spatial detail required to explore the impacts of other natural disasters such as floods. To do so, for instance, by linking HILDA data to satellite data as has been done for surveys in other countries (Guiteras *et al.* 2015), a finer geographic identifier than currently available is needed.

3 (>117 and ≤159), 4 (>159 and ≤199), 5 (>199). Other studies also gauge cyclone exposure using maximum wind speed (Hsiang & Narita 2012; Currie & Rossin-Slater 2013; Hsiang & Jina 2014).[6]

To keep the analysis manageable and to deal with the relative rarity of yearly cyclones, we combine several categories into two overlapping groups: all cyclones, and category 5 (most severe) only. Each group is then combined with the nearest cyclone path distance to the individual's residential postcode. As a result, we have a set of six variables measuring cyclone exposure, each of them is identified by the cyclone category and distance to the cyclone eye. Furthermore, due to the infrequent nature of yearly cyclone occurrences during the study period, we employ a dummy variable indicating whether a cyclone was recorded within the individual's residential postcode in the 12 months preceding the survey date.[7] For instance, among the six cyclone exposure measures used in this study, the strongest one is a binary variable indicating whether an individual's residential postcode was within 30 km of a category 5 cyclone path in the preceding year.

In the main analysis, we focus on cyclones recorded within 12 months before the interview date. This maintains result traceability and aligns with the timing of some outcomes in HILDA, like natural disaster related home damage, which refers to "the past 12 months".[8] Because survey dates vary by individuals, individuals living in the same postcode may have different exposures to the same cyclone within the same survey wave.

[6] While this approach offers efficiency in managing a large number of cycle exposure variables and aligns with data availability constraints, it does not consider the influence of other co-occurring and currently unobserved hazards, such as torrential rain, flooding, and storm surge. Similar reasoning had led to its widespread use in previous international studies (Currie & Rossin-Slater 2013; Franklin & Labonne 2019; Groen *et al.* 2020; Deryugina & Marx 2021).

[7] Within our final sample, of the individuals experiencing at least one cyclone within 100 km annually, only 4% faced multiple cyclones during the same period. We assign the cycle with the highest category for individuals facing multiple cyclones per year.

[8] The majority of HILDA interviews (90%) were conducted during the concentrated period of August to October (See Appendix Figure A1). Almost all (95%) of observed cyclones, encompassing all categories, occurred within the November-April timeframe during the study period. See Appendix Table A1 for variable description and summary statistics.

3.3. Outcome variables

We consider six housing-related variables. The first variable measures whether the respondent's home was damaged or destroyed by a weather-related disaster such as flood, bushfire or cyclone in the past 12 months.[9] While this variable is only available from wave 9 (Summerfield *et al.* 2023), we introduce it first because cyclone is specifically mentioned in the questionnaire, using this variable allows us to capture any direct effects of cyclones. This conveniently provides a verification test for our matching procedure before we move on considering other outcomes.

To gauge the potential impacts of cyclone exposure on migration, we utilise five indicators. These include a variable capturing the individual's relocation intention, denoted as "likely to relocate"[10] and four variables describing actual relocation. Specifically, we follow Nguyen *et al.* (2024) to consider four variables capturing a residential move. The first variable is an indicator describing whether an individual makes any residential change in the period between the two interview waves (henceforth referred to as "residential relocation"). We additionally employ a measure called "relocation distance" to capture the distance of the residential movement. This measure has been calculated by the custodian of HILDA, using a great circle formula applied to latitude and longitude of the previous and current geocoded addresses (Summerfield *et al.* 2023). We further distinguish a residential move by geographical location, defining whether (i) the individual moves across Local Government Areas (LGA)[11] between two adjacent survey waves ("inter-LGA relocation") or (ii) the individual relocates from one state/territory in one survey wave to another state/territory in the next survey wave ("inter-state

[9] This metric stems from responses to a query asking, "Did any of these happen to you in the past 12 months?" and prompt "A weather-related disaster (e.g., flood, bushfire, cyclone) damaged or destroyed your home".
[10] To ascertain potential movers, we designate individuals who responded "Likely" or "Very likely" to the query "How likely is it that you will move in the next 12 months?" as "likely to relocate." The remaining respondents who selected "Very unlikely", "Unlikely", or "Neither / not sure" form the comparison group.
[11] LGAs are Australian Bureau of Statistic (ABS)'s approximation of gazetted local government boundaries as defined by each state and territory local government department. In 2020, there were 562 LGAs in Australia.

relocation"). It is noteworthy that, except the relocation intention variable, which is available in all waves, all above residential relocation variables are available from wave 2 of HILDA onwards.

3.4. Sample

This paper's unit of analysis is the individual, and our baseline analysis focuses on states and territories impacted by at least one cyclone during the study period. This restriction improves the efficiency of individual fixed effects estimates for exposed individuals, as cyclone exposure doesn't vary over time for those in unaffected regions (Wooldridge 2010). Consequently, New South Wales, Queensland, Western Australia, and Northern Territory form our baseline sample, while states further south of the equator are excluded (Figure 1 shows the hit map of cyclones during the study period). Additionally, we require individuals to be 15 years or older because younger individuals are not interviewed in HILDA. Moreover, they need to be observed at least twice within the study period, as our primary empirical model relies on individual fixed effects. Combining these restrictions, the final sample size varies depending on the outcome. For example, we have a longitudinal sample consisting of 204,466 individual-year observations from 21,815 unique individuals collected across 22 years to examine the impact of cyclone on residential relocation intention outcome. This is the largest sample size in the study.

3.5. Sample representativeness

In our study design, concerns arise regarding the potential influence of cyclone exposures on participants' likelihood of being interviewed in subsequent waves. To mitigate this concern, we adopt an individual Fixed Effects (FE) model similar to Equation (1) (more on this in the following section). The primary dependent variable signifies whether individuals were not interviewed in the following survey wave for any reason. Addressing another concern regarding the potential impact of cyclone exposures on international migration, we introduce an additional dependent variable identifying whether non-interviews were due to being overseas. Explanatory variables comprise current and lagged indicators of exposure to any cyclone within 30 km of its eye, alongside other time-variant variables specified in Equation (1). The sample is restricted to individuals in states and territories impacted by at least one cyclone during the study period.

In accordance with previous research (Nguyen & Duncan 2017), the estimates presented in Appendix Table A2 disclose notable demographic differences, notably in age and education, between the included and excluded samples, with the direction and magnitude of these differences varying depending on the selected dependent variable. Nevertheless, the maximum R-squared value of 0.02 implies a minimal quantitative impact of the included variables. Notably, all estimates pertaining to current and lagged cyclone exposure variables exhibit joint statistical insignificance, evident from Wald test p-values exceeding 0.20. Furthermore, a negative and marginally statistically significant estimate ($p<0.10$) is observed for the variable representing one-year lagged exposure to cyclones within a 30 km radius in the regression analysis of attrition for any reason. This finding suggests a slightly elevated likelihood of inclusion in our sample for individuals affected by cyclones in the previous year.

Overall, these findings assuage concerns regarding potential cyclone-induced sample selection bias. Additionally, the statistically insignificant estimates pertaining to all cyclone exposure variables concerning attrition due to overseas relocation suggest that cyclone exposure does not influence international migration.

4. Empirical model

The following econometric model is employed to investigate the impacts of cyclones on the outcome Y by individual i, who resided in postcode p, at time t:

$$Y_{it} = \alpha + \beta Z_{i(p)t} + X_{it}\gamma + \delta_i + \varepsilon_{it} \qquad (1)$$

where $Z_{i(p)t}$ is a binary variable capturing whether the postcode p has been hit by a cyclone in the previous year. X_{it} is a set of time-variant explanatory variables. δ_i is an individual time-invariant unobservable factor and ε_{it} is the usual idiosyncratic term. α, β and γ are parameters to be estimated.

To address the potential counfouding effects, we include in X_{it} a parsimonious number of individual and household level time-variant variables. These include the individual's age (and its square), marital status, education levels and the number of household members. Due to the difference in survey time and the time horizon that some of the outcomes are measured (e.g., home damage is measured in the previous year and residential relocation intention refers to the next 12 months), we control for month of interview in all regressions. We further address the potential temperal differences in outcomes by controlling for a list of survey year dummies. Moreover, we deal with likely regional differences by including state/territory dummies in Equation (1). We additionally control for differences in local socio-economic environments which may influence the individual behaviours by including regional unemployment rates, a relative socio-economic disadvantage index, and whether the individual lived in a major city in all regressions.

As we observe multiple observations per individual, we apply an individual FE regression technique which controls for individual heterogeneity, including individual residential preferences, to Equation (1). Our ability to control for individual unobservable time-invariant factors is particularly important because previous studies have found that areas that are more likely to be hit by a natural disaster tend to be more disadvantaged (Dell *et al.* 2009; Currie & Rossin-Slater 2013; Botzen *et al.* 2019). Our estimates of the cyclone impact (β) are identified from yearly fluctuations in cyclones within a postcode for the same individuals. This, coupled with the randomness of specific locations impacted by cyclones despite their spatial clustering, strengthens causal inferences (Deschenes & Greenstone 2007; Dell *et al.* 2014; Jessoe *et al.* 2018).

As discussed in Section 3, we measure the cyclones recorded within 12 months before the survey date. Because survey dates vary by individuals interviewed during the same wave (See Appendix Figure A1), using survey dates in this matching exercise strengthens the identification assumption. In particular, due to differences in dates of surveys and cyclones, individuals living in the same postcode may have different exposures to the same cyclone. Because the treatment varies by the same individual over time, standard errors are clustered at the individual level to address the potential serial correlation issue (Cameron & Miller 2015). In robustness checks, we also present largely similar results, with standard errors clustered at the postcode level or with additional control for postcode fixed effects.

5. Main results on impacts of cyclones on residential outcomes

5.1. Descriptive results

Table 1 presents descriptive statistics for key variables, split by cyclone exposure status. Only 4% of individuals in our analytical sample experienced at least one cyclone within 100 km of their home during the study period, forming our "treated" group.[12] Those affected tend to be younger, less educated, have smaller families, and live in rural areas compared to the unaffected "control" group. Notably, while unemployment rates are lower in regions encompassing the "treated" group, these areas exhibit lower overall socioeconomic status as measured by the Socio-Economic Indexes for Areas (SEIFA) decile. This aligns with international evidence (Currie & Rossin-Slater 2013; Dell *et al.* 2014) that disadvantaged regions, as measured by

[12] Table 1 reveals that 8,601 year-observations from 5,952 unique individuals qualify as treated, constituting a sufficiently large sample to capture the effects of cyclones. Furthermore, the last column in Appendix Table A1 demonstrates that despite the relatively infrequent occurrence of yearly cyclones during the study period, our final sample includes a substantial number of individuals exposed to other cyclones, allowing for credible detection of potential effects (Wooldridge 2010). Notably, the minimum number of individuals in the treated group, 487, is observed for those exposed to a category 5 cyclone within 30 km from its eye.

SEIFA index, are more prone to natural disasters. Therefore, accounting for individual fixed effects like residential preferences is crucial when studying cyclone impacts (Deschenes & Greenstone 2007; Dell *et al.* 2014; Botzen *et al.* 2019; Nguyen *et al.* 2021).

Table 1 reveals stark differences in several outcomes between cyclone-exposed and unaffected individuals. As expected, exposed individuals report higher rates of natural disaster-related home damage. They are also more likely to report planning to move location within the year and to have relocated since the last survey. However, as discussed in Section 4, these disparities may not solely reflect cyclone impacts, but rather pre-existing differences influencing both exposure and outcomes. The following analysis tackles this critical issue.

5.2. Regression results

Our preferred FE regressions[13] (Table 2), which account for both observable time-variant and unobservable time-invariant factors, reveal notable effects on selected residential outcomes. For instance, individuals exposed to cyclones exhibit significantly higher probabilities of self-reported natural disaster-related home damage across all six exposure measures ($p < 0.01$, Panel A, Table 2). Further analysis reveals crucial nuances. The damaging impact of cyclones scales positively with cyclone intensity. For example, holding distance to the eye constant at 30 km, the estimated probability of home damage increases by approximately three-fold from 6 percentage points (pp) for a cyclone of any category to 17 pp for a category 5 cyclone. Conversely, distance provides some mitigation. Individuals residing within 100 km of a category 5 cyclone's eye are less than twice as likely to report home damage compared to those at 30 km. These findings initially support the validity of our algorithm employed to link HILDA

[13] While concerns may exist about limited variation in cyclone exposure measures affecting our individual FE model, these are unfounded. First, significant within-individual variation shown in Appendix Table A1 demonstrates diverse experiences within the exposed group. Second, FE regressions deliver lower standard errors for cyclone exposure compared to Random Effects models (Appendix Table A3), indicating sufficient variation for FE estimation. Finally, unreported Hausman test F-statistics conclusively favour FE models across all cases. Thus, our data readily support employing an FE model for robust analysis (Wooldridge 2010).

and historical cyclone data. Furthermore, they corroborate the Australian Bureau of Meteorology's descriptions of escalating cyclone impact, ranging from “negligible house damage” for category 1s to “extremely dangerous with widespread destruction of buildings” for category 5s (BOM 2024).

Further mirroring the escalating scale of cyclone impact, our findings also reveal a nuanced relationship between cyclone exposure and individual relocation intention (Panel B, Table 2). For example, individuals directly impacted by category 5 cyclones display the strongest and most statistically significant rise in their intention to relocate within the following year. Moreover, echoing the distance-dependent effect on home damage, the estimated impact of cyclones on relocation intention diminishes substantially as distance from the eye increases. For instance, the estimated likelihood of moving nearly halves when comparing individuals residing 30 km and 100 km from the eye of a category 5 cyclone. This highlights the crucial role of both cyclone intensity and geographical proximity in shaping individual desired responses to these natural disasters.

Our analysis extends beyond intentions, delving into the actual residential movements triggered by cyclones (Panels C to F, Table 2). While not all estimates reach statistical significance, the overall picture reveals a compelling interplay between cyclone intensity, geographical proximity, and residential movement. For instance, individuals residing within 30 km of any cyclone's eye, or within 60 km of a category 5 cyclone, are significantly more likely ($p<0.10$) to have changed addresses since the last survey compared to unaffected individuals. Relocation distance further underscores this pattern. Those within 30 km of any cyclone's eye moved an average of 31 km, while those facing the wrath of a category 5 at the same distance moved 53 km, highlighting the escalating impact with cyclone intensity. Moreover, cyclone-affected individuals exhibit a higher propensity for longer-distance moves, crossing LGA or state/territory boundaries. This pattern is corroborated by estimates for inter-state relocation, which are statistically significant at the 1% level for those within 30 km of any cyclone and increase in magnitude for category 5 cyclones. The estimates, when statistically significant, exhibit substantial magnitude. For example, individuals impacted by any cyclone within 30 km from its eye are 1.64 pp more likely to relocate to other states, marking roughly a 36% increase over the sample mean of 4.54%.

In summary, the regression results outlined above demonstrate that cyclones, particularly those of heightened severity and proximity to homes, statistically significantly and amplify intentions for relocation and actual migration. Moreover, when considered alongside a previous observation indicating the negligible impact of cyclones on attrition due to overseas relocation, it suggests that cyclones primarily stimulate long-distance domestic migration. This aligns with evidence from studies on hurricane-induced domestic migration in the US (Sheldon & Zhan 2022), as well as broader international research indicating migration as a coping strategy among cyclone-affected individuals in developing nations (Gröger & Zylberberg 2016; Spencer & Urquhart 2018; Mahajan & Yang 2020). Our novel findings regarding the significant impact of cyclones on domestic relocation hold particular relevance for Australia, where the awareness of relocation risks associated with cyclones lags behind other natural disasters such as heatwaves, bushfires, and floods (Zander *et al.* 2020).

6. Robustness checks

To ensure the reliability of our findings, we employed diverse sampling and specification tests. For conciseness, we present results based on one cyclone exposure measure: living in a cyclone-affected postcode within 30 km of the eye, 1 year prior. We found analogous results with other metrics, which are available upon request. Our first sampling test is to include in the regression only individuals residing in LGAs hit by at least one cyclone within 100 km during the study period. This test is to address a concern whether the baseline sample contained sufficient cyclone exposure variation. The results obtained from this more restrictive sample are reported in Panel B1 of Appendix Table A3. Reassuringly, the results align closely with the baseline (re-reported in Panel A) in terms of both magnitude and statistical significance. To further validate our findings, we also analysed the entire dataset (Panel B2) and again observed similar outcomes.

We proceed to examine the robustness of our results through seven specification checks. Firstly, we augment our individual FE regression by incorporating postcode dummies to address concerns regarding potential associations between cyclone exposure, outcome, and unobservable time-invariant factors at the postcode level (results in Panel C1). Secondly, we cluster the estimates at the postcode level rather than the individual level in the baseline analysis (Panel C2). Subsequently, we employ a regression model lacking individual fixed effects, represented by either a pooled Ordinary Least Squares (OLS) regression estimator, as depicted in our third robustness check (Panel C3), or a Random Effects (RE) model, as outlined in the fourth robustness check (Panel C4).[14]

Fifth, we exclude certain time-variant variables, such as education, marital status, household size, and urban residency, which may be influenced by cyclone events from the regression (Panel C5). Sixth, we introduce an interaction term between state/territory and year dummies into the baseline specification (Panel C6). Seventh, we apply a RE logit model[15], acknowledging the binary nature of the five dummy outcomes utilised in the main analysis (Panel C7). Across these seven specification tests (Panels C1-C7, see Appendix Table A3), our findings exhibit robustness to variations in model specifications and estimation methodologies.

[14] To account for potential confounding effects, we incorporated time-invariant variables, including gender and migration status, into this specification. The Hausman test (F-statistics unreported) confirmed strong correlation within individual error terms, further validating the use of an individual fixed effects model.

[15] A FE logit model failed to converge, probably due to the relatively large sample size and a large number of dummy variables used. As documented above, we control for various time-invariant variables in this RE regression. Moreover, we report the estimates in marginal effects after logit regressions to make them comparable to those in the baseline regression.

7. Heterogeneity

To enhance our understanding of the potential channels through which cyclones affect residential outcomes, we investigate the likely heterogeneity across diverse sub-populations. We achieve this by estimating an individual FE model (1) for two distinct groups defined by each of eight individual, household or regional characteristics.[16] Building on previous evidence suggesting potential differential impacts of climatic factors on human behaviours (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020), our individual characteristics encompass gender (male vs. female) and age group (young vs. old, classified relative to the median population age). Furthermore, household straits include homeownership status (renters vs. homeowners), income group (lower income vs. higher income households, defined relative to the median of household income)[17], home insurance status (insured vs. uninsured)[18], urban/rural residence (major city vs. rural area), and distance to the coast ("coastal areas" vs. "inland areas", with the latter defined as postcodes where the distance from postcode centroids to the coastline exceeds the median distance (approximately 10 km)). To mitigate concerns that cyclones and their subsequent effects on individual or household behaviours (e.g., migration or insurance acquisition) might influence sub-population classification, we categorize individuals based on

[16] This heterogeneous analysis focuses on these specific characteristics due to their strong theoretical and empirical rationales for influencing cyclone response. Data availability also influenced the selection, as some variables are collected less frequently (e.g., household wealth). It is important to note that small sample sizes in some subgroups require cautious interpretation of the results.

[17] To account for both temporal inflation and variations in household size, we leverage inflation-adjusted and size-equivalised household income. Similarly, all other monetary variables are transformed to reflect their purchasing power in 2010.

[18] Insurance expenditure data are available from Wave 6 onwards. Approximately 90% of households in the final sample reported positive annual expenditures on home, contents, and/or motor vehicle insurance during the study period. To enhance the heterogeneity of the analysis, particularly regarding housing outcomes, we aimed to isolate households with a higher likelihood of possessing home or content insurance coverage. Consequently, we employed a binary classification scheme, categorizing households spending $1,250 or more (adjusted to 2010 prices) annually on combined home, contents, and motor vehicle insurance as "insured" and the remaining households as "uninsured". This threshold aligns with the average annual comprehensive car insurance premium for a family household with a young driver during the same period ($1,733 in 2023 prices, equivalent to $1,250 in 2010 prices, as referenced from https://www.canstar.com.au/car-insurance/what-does-car-insurance-cost/. Additionally, our data (more on this later) suggest almost all (90%) households have comprehensive vehicle insurance coverage, implying that households exceeding the $1,250 threshold are likely to possess home or content insurance. Notably, this cutoff point closely coincides with the median annual expenditure on combined insurance across all households in the sample, conveniently dividing the group into roughly equal sub-populations for robust heterogeneous analysis.

the values of time-variant variables (excluding age) observed at their first appearance in the sample.

The primary regional characteristic is defined by whether the individual's residing postcode experienced any cyclone in a radius of 100 km from its eye within the past 30 years. We deliberately opt for historical cyclone exposure, rather than current or future exposure, to capture the pure effects of historical climatic factors in forming behaviours of current residents. This understanding is crucial for preparedness and policy planning for future cyclones in regions with different historical cyclone exposure (Dell *et al.* 2014; Carleton & Hsiang 2016). Moreover, a 30-year window is chosen to reflect the local area's long-term climatic pattern and conveniently results in two sub-populations with roughly equal sizes ("cyclone-free areas" and "cyclone-prone areas") for more reliable group-specific estimates.

This section employs a single cyclone exposure indicator for brevity and demonstration purposes: whether individuals encountered a cyclone within 30 km of its eye.[19] Figure 2 presents descriptive statistics and regression estimates revealing notable differences in the impact of cyclone exposure on housing outcomes across various subgroups within the population. Notably, gender seems to play a significant role in shaping individuals' relocation behaviours. Males, characterized by inherently higher mobility as suggested by the mean figures in each panel, display a greater responsiveness to cyclones compared to females. This is evidenced by both larger estimates and higher statistical significance for relocation frequency and average relocation distance among males. This finding aligns with studies conducted in

[19] This specific cyclone exposure measure is selected for its representativeness in terms of both severity and frequency compared to other measures employed in this study. Additionally, pooled regression results (Table 2 Column 1) demonstrate its statistically significant impact on numerous outcomes evaluated. However, an exception arises regarding the residential relocation intention outcome, where the cyclone exposure measure is presented by whether individuals were affected by a category 5 cyclone within 100 km of its eye. This particular approach is adopted to facilitate a more meaningful heterogeneous analysis. Notably, consistent with estimates for the overall population, the utilisation of whether individuals encountered a cyclone within a 30 km radius of its eye as the cyclone exposure measure results in statistically insignificant sub-population estimates for the residential relocation intention variable across all cases.

diverse contexts including Nigeria (Dillon *et al.* 2011) and Pakistan (Mueller *et al.* 2014), and Indonesia (Thiede & Gray 2017), which found that males are more likely to migrate in response to environmental stressors such as heat extremes. Similarly, Boustan *et al.* (2012) report increased migration of young men from Central America and the Caribbean to the US following hurricanes.

While males exhibit a greater propensity for relocation, our results reveal a seemingly counterintuitive trend of slightly higher prevalence for LGA and interstate relocations among females. This unexpected finding can be attributed to two key factors. First, the majority of the population remains stationary, resulting in a skewed distribution of relocation distances towards zero, which amplifies even small differences in short-distance relocation rates. Second, females exhibit a generally lower overall propensity for relocation compared to males, making even minor increases in their short-distance migration more statistically noticeable. This interpretation is further supported by our unreported results, which show a higher likelihood of intra-LGA relocations among males. These findings suggest that gender differences in relocation patterns are nuanced and dependent on the spatial scale considered.

Consistent with the observed higher mobility of younger individuals (evidenced by mean figures across panels), our analysis reveals a significant age-based pattern in relocation behaviours following cyclone exposure. Only estimates for younger age groups exhibit positive and statistically significant coefficients ($p<0.05$), indicating a greater propensity for relocation in response to cyclones. This finding aligns with previous research, such as studies examining the impacts of hurricanes in the US (Logan *et al.* 2016) and droughts or hurricanes in Northern Latin America and the Caribbean (Baez *et al.* 2017), which similarly found elevated relocation rates among younger populations.

In line with their inherently higher baseline relocation intention and actual mobility, as illustrated in Figure 2, renters exhibit a notably heightened inclination and propensity to relocate subsequent to cyclone exposure. This pattern is evident in statistically significant positive estimates for relocation intention ($p<0.01$), relocation distance ($p<0.10$) and inter-LGA and interstate relocations (both $p<0.05$). Notably, renters appear to be the only group exhibiting a statistically discernible increase in relocation after cyclones. Conversely, homeowners, who might be considered a "trapped population" due to the substantial investment tied to homeownership (Black *et al.* 2013), display a muted response. This finding, to our knowledge, represents a novel contribution to the literature, in part due to the utilisation of individual-level and comprehensive panel data.

While not directly comparable, our results resonate with research supporting the "housing lock hypothesis," which proposes that homeowners experiencing decreased home equity exhibit diminished relocation probability (Bloze & Skak 2016; Bernstein & Struyven 2022). In our specific context, cyclone-affected homeowners may experience a reduction in their home equity (Beltrán *et al.* 2019), potentially due to documented direct home damage, consequently limiting their ability to relocate. Renters, however, lack this specific obstacle. This potential disparity might explain why only renters demonstrate an increase in relocation following cyclone exposure.

Disaggregating results by income level reveals no significant differences in migration rates between individuals from high- and low-income families, as reflected by similar mean figures. Additionally, reported home damage post-cyclones shows no substantial disparities across income groups. However, a notable pattern emerges concerning relocation intentions and behaviours. Specifically, lower-income individuals exhibit a heightened inclination to migrate when facing a category 5 cyclone within 100 km from its eye, as demonstrated in Panel B. In contrast, individuals from more affluent families demonstrate a significantly higher propensity to relocate, especially for inter-LGA and interstate moves. While positive cyclone exposure estimates are observed for both income groups, they are markedly larger and statistically significant ($p<0.05$) only for high-income individuals. This trend echoes previous research, such as the US study by Sheldon and Zhan (2022), indicating increased relocation among wealthier populations following natural disasters. These findings suggest that economically disadvantaged individuals may lack the resources for post-disaster relocation, emphasizing the necessity for targeted support policies to assist vulnerable populations.

Subgroup analysis based on insurance status reveals distinct patterns in residential adjustments following cyclone exposure. While individuals without insurance report slightly higher rates of home damage compared to their insured counterparts when exposed to cyclones within 30 km, the most notable disparity lies in relocation intentions and behaviours. Positive estimates across various relocation measures are evident for both insured and uninsured individuals. However, statistical significance ($p<0.05$) is observed solely for the uninsured group. This differing impact on migration may stem from preexisting disparities between the insured and uninsured populations. Baseline data indicate that uninsured individuals demonstrate greater intention and mobility, potentially influencing their response to cyclones. Additionally, insurance coverage may alleviate the financial burden associated with cyclone-induced repairs, thus reducing the imperative to relocate (Kousky 2019). Consequently, the absence of observed relocation among insured individuals post-cyclone exposure may be attributed to the mitigating effect of insurance. Further exploration of this potential mechanism will be undertaken in Section 8.

Our analysis reveals a stark disparity in the impact of cyclones on rural and urban residents. While rural individuals consistently report higher rates of disaster-related home damage - twice the average as seen in mean figures - this effect intensifies significantly when exposed to cyclones within 30 km of the eye, exhibiting a fivefold increase. Non-overlapping confidence intervals in Figure 2 visually corroborate these statistically significant differences ($p<0.05$). Conversely, urban residents affected by a category 5 cyclone with a 100 km radius from its eye show a statistically significant greater intention to relocate than rural counterparts. Furthermore, subgroup estimates reveal intriguing spatial nuances in relocation patterns across these groups. Urban residents exhibit a greater propensity to relocate compared to their rural counterparts, covering longer distances on average, as evidenced by larger and statistically significant estimates for them. Conversely, rural inhabitants demonstrate a statistically significant increase in out-migration following cyclone exposure, primarily to other LGAs or states. This phenomenon is reflected in quantitatively larger estimates and higher levels of statistical significance for rural populations compared to urban residents.

The observed inclination of rural residents to relocate to other LGAs or states resonates with theoretical frameworks proposed by Harris and Todaro (1970) and empirical studies conducted by Marchiori *et al.* (2012), among others. These models suggest that agriculture, particularly in developing nations, serves as a conduit through which natural disasters impact migration. Given that rural livelihoods rely heavily on agricultural activities, which cyclones disrupt more than urban occupations, heightened migration among rural populations is plausible. However, research findings by Nguyen and Mitrou (2024), employing a methodology similar to ours, indicate an insignificant impact of cyclones on rural income, while urban residents experience a marginal decrease. This implies that income might not be the primary catalyst for observed migration differences between rural and urban populations in developed countries like Australia. Such observations align with a study by Falco *et al.* (2019), which demonstrate that adverse shocks to agricultural productivity resulting from climate fluctuations significantly boost emigration from developing countries, particularly affecting impoverished nations. In Section 10, we will explore alternative potential channels through which cyclones might influence migration.

Sub-group estimates based on proximity to the coastline unveil significant disparities in cyclone impacts on home damage and relocation between coastal and inland residents. Notably, individuals in coastal regions exhibit a much lower likelihood of reporting home damage when affected by a cyclone within 30 km of its eye. Conversely, only coastal area residents demonstrate a heightened desire and actual propensity to relocate, as evidenced by statistically significant estimates ($p<0.01$) exclusively for this group. The discovery of a significant cyclone-induced relocation impact among individuals residing nearer to the coastline is consistent with the notion that cyclones tend to lose power as they move inland (BOM 2024). Moreover, it aligns with the compounded effects of other hazards, such as storm surge, commonly associated with cyclones, which are particularly pertinent for coastal areas (Ouattara & Strobl 2014).

While individuals residing in historically cyclone-free and cyclone-prone regions exhibit no significant disparities in reported home damage, intriguing patterns emerge regarding relocation intentions and actual relocation behaviour. While estimates are of similar magnitude for residents in both historically cyclone-free and cyclone-prone areas, only the estimate for residents from the cyclone-prone regions is statistically significant at 1% level. Conversely, residents in regions previously unexposed to cyclones, characterised by inherently lower baseline mobility, display statistically significant and substantial increases in both relocation distance and interstate relocation probability upon encountering a novel event. This heightened vulnerability is demonstrably stronger compared to their counterparts in historically exposed regions, as evidenced by statistically significant and larger coefficient estimates associated with the former group. Specifically, analysis reveals that individuals from historically protected regions migrate an average of 180 km further and exhibit a sevenfold increase in the likelihood of interstate relocation compared to those from historically exposed areas.

To our knowledge, this study stands as the first to document the differential migration impacts of cyclones based on a region's historical exposure within this specific literature. This finding aligns with the broader concept of acclimatisation documented in the climate change literature, where populations routinely subjected to environmental threats tend to exhibit less pronounced behavioural responses to new pressures (Hsiang & Narita 2012; Dell *et al.* 2014). Our analysis suggests that individuals lacking prior experience with extreme events, even within historically protected regions, may be particularly susceptible to displacement when encountering them for the first time. This intriguing discovery contributes to an understanding of the multifaceted dynamics of human behaviour in the face of climate threats and underscores the critical role of historical context in shaping responses to extreme events.

8. Cyclone exposures and insurance acquisition

Building on our previous analysis, which demonstrated only individuals without pre-existing insurance relocate in response to cyclones, this section investigates further the potential role of insurance as a coping mechanism (see Kousky (2019) or Kraehnert *et al.* (2021) for reviews). We hypothesize that insurance alleviates the financial strain associated with repairing cyclone damage to the primary residence, thereby reducing relocation pressures. To test this hypothesis, we directly examine the influence of cyclone exposure on insurance attitudes and behaviours, and their subsequent association with costs associated with such damage. We employ a modified version of Equation (1) by incorporating both current and lagged cyclone exposure variables to assess their cumulative impact on a range of insurance-related variables. The HILDA survey is particularly well-suited for this analysis due to its longitudinal nature and repeated measures on insurance-related variables. This allows for the implementation of individual FE models, effectively isolating the causal effects of cyclone exposure on insurance behaviours. The empirical evidence presented in this study addresses a critical gap in existing knowledge because there is a notable lack of rigorous research exploring the impact of natural disasters on insurance behaviours in the Australian context. Moreover, the broader international literature on natural disaster insurance and its role in recovery remains surprisingly thin (Kousky 2019; Kraehnert *et al.* 2021).

In this analysis, we examine six insurance-related variables. The first two variables gauge an individual's conviction regarding the essential nature of “having home and contents insurance,”[20] while another variable indicates whether the individual or their family “has home contents insurance” at the time of the survey. We additionally employ two analogous variables pertaining to “comprehensive motor vehicle insurance” for two reasons: (1) cyclones, as demonstrated in Section 5, can damage vehicles alongside homes, and (2) HILDA combines information on vehicle and home/contents insurance expenditure.

A fifth insurance-related monetary variable is introduced, capturing “annual household expenditure on other insurance such as home, contents, and motor vehicle”.[21] This encompasses a broader range of insurance beyond the previously examined specific coverage types. Additionally, a sixth variable is included, indicating whether the household spent $1,250 or more annually on combined home, contents, and motor vehicle insurance (adjusted to 2010 prices). As established in the preceding section devoted to heterogeneity analysis, this binary variable acts as a potential proxy for possession of home or contents insurance coverage.

Table 3 presents compelling evidence that cyclone exposure significantly influences individuals' attitudes towards and behaviours regarding insurance. Analyses reveal that experiencing a cyclone positively influences the likelihood of believing home and contents insurance is essential (Panel A). Importantly, this effect intensifies with cyclone severity, as

[20] The construction of the first and third variables in this section follows the response options to the prompt: “Next I am going to read out a list of items and activities, and I want you to tell me whether you think each of these are things that are essential – things that no one in Australia should have to go without today.”, in reference to “home contents insurance” and “comprehensive motor vehicle insurance”, respectively. These variables are only available in Waves 14, 18 and 22.

[21] Our data on insurance and repairs come from the household expenditure module available from Wave 5 onwards. All surveyed members responsible for paying bills report these expenses. When multiple household members respond (roughly 25% of cases), we average their reported amounts. Since the expenditure questions focus on typical weekly spending, we convert expenses to annual by multiplying by 52 weeks. We calculate home insurance from “other insurance (home/contents/motor vehicle)” (starting Wave 6) and home repairs from “home repairs/renovations/maintenance.” Prior studies have utilised similar measures (Nguyen & Duncan 2017; Mitrou *et al.* 2024). Although we have used established methods and data sources, the small sample size and potential measurement errors necessitate caution when interpreting the results.

category 5 events show the strongest impact. While not all estimates attain statistical significance, likely due to limited sample sizes in some categories, the overall pattern suggests increased acquisition of home and contents insurance following cyclone exposure (Panel B). This trend aligns with similar observations regarding comprehensive motor vehicle insurance (Panels C and D).

Consistent with these findings, Panel E demonstrates a significant increase in annual insurance expenditure by households exposed to cyclones. Notably, this increase correlates with both the intensity and proximity of the cyclone, suggesting higher spending for those closer to or experiencing more severe events. Individuals residing within 30 km of a category 5 cyclone, for instance, incur significantly higher insurance costs compared to those further away. These findings echo our earlier observations of escalating home damage and relocation intentions associated with cyclone intensity and proximity.

Finally, Panel F reinforces the link between cyclone exposure and insurance acquisition by indicating a statistically significant rise in likely home and contents insurance coverage among affected households. Notably, this increase is most pronounced for individuals exposed to category 5 cyclones, both concurrently and in the previous year. Taken together, these findings strongly suggest that cyclones function as a catalyst for individuals to recognize the value of insurance and actively seek coverage to mitigate future risks.

Building upon the previous findings, we investigate whether acquired insurance serves as a protective shield against future cyclone-induced repair costs. To do so, we employ an individual FE model similar to Equation (1), incorporating a one-year lagged insurance status variable and its interaction with current cyclone exposure measures. This addresses potential endogeneity concerns, as our earlier analysis revealed increased insurance acquisition following cyclone exposure. The model is estimated using annual household expenditure on "home repairs/renovations/maintenance," acknowledging the limitations of this aggregated measure and its potential ambiguity regarding cyclone influence. Nevertheless, the interaction term between lagged insurance status and current cyclone exposure offers valuable insights into the mitigating effects of insurance.

As hypothesized, the results reported in Table 4 provide suggesting evidence in favour of insurance effectiveness. The statistically significant ($p < 0.01$) positive estimates of lagged insurance status indicate that insured individuals spend approximately $390 more per year on home repairs, renovations, and maintenance in the following year compared to uninsured counterparts. Notably, all interaction terms exhibit negative coefficients, with statistical significance observed for more damaging cyclones. These negative and statistically significant estimates imply that insured individuals facing a cyclone experience significantly lower repair costs (exceeding $1,000 annually) compared to their uninsured counterparts. Conclusively, this section demonstrates that individuals proactively acquire insurance post-cyclone, and this acquired protection demonstrably mitigates the financial burden associated with future cyclone-induced home repairs.

Having identified home and content insurance acquisition as a mitigating mechanism employed by cyclone-affected individuals, as previously explored in the heterogeneous analysis of cyclone impacts on migration, our next endeavour is to investigate who are more likely to employ this alternative coping strategy. Similar to previous methodologies, by contrasting likely differential variances across various individual, household, and local characteristics as delineated earlier, this extensive heterogeneous analysis illuminates the potential channels through which cyclones affect insurance purchase and identifies potential barriers to this coping strategy (Kousky 2019; Carleton *et al.* 2022).

Sub-group estimates, as depicted in Figure 3, suggest various factors influencing the differential insurance acquisition in response to cyclones.[22] For instance, male and younger individuals demonstrate a higher propensity to purchase home-related insurance against future cyclone risks, as evidenced by larger and more statistically significant estimates for this demographic. Moreover, as expected, only homeowners, who exhibit over twice the likelihood of having home insurance at baseline according to mean figures, are statistically significantly ($p < 0.01$) more likely to obtain home-related insurance when faced with a category 5 cyclone within 100 km of its eye.

Similarly, only individuals from wealthier households, who are approximately 50% more likely to have home insurance at baseline, are statistically significantly ($p < 0.01$) more likely to purchase insurance when impacted by a cyclone of the same magnitude. Recall that earlier findings indicated that only cyclone-affected individuals from higher-income households are statistically significantly more likely to migrate. Together, these findings convey that only individuals from more economically advantaged backgrounds can employ the two identified coping strategies (i.e., migration and insurance acquisition), reinforcing the need for targeted support policies to assist vulnerable populations. Remarkably, there is no significant disparity in insurance acquisition between previously insured and uninsured individuals in response to cyclones, as the positive estimates hold statistical significance at the 5% level and are of equivalent magnitude for both groups.

Moreover, insurance purchase is predominantly utilised by residents in rural or inland areas, as indicated by statistically significant estimates ($p < 0.01$) for this demographic exclusively. The

[22] For the sake of conciseness and illustrative purposes, this analysis concentrates on a single measure of cyclone exposure, specifically whether individuals experienced a category 5 cyclone within 100 km of its eye. This specific measure is chosen based on prior findings indicating that insurance acquisition exhibits the most notable response to it. Furthermore, to ensure meaningful and robust heterogeneous analysis, we utilise a dummy variable indicating whether the household spent $1,250 or more annually on combined home, contents, and motor vehicle insurance (adjusted to 2010 prices) as the sole insurance outcome here.

finding that only residents in rural or inland areas are statistically significantly more likely to purchase insurance is consistent with earlier evidence of a greater impact of cyclones on home damage for this group. Furthermore, only residents in cyclone-prone areas are statistically significantly ($p < 0.01$) more likely to obtain insurance when facing a new cyclone. This finding aligns with theoretical projections and empirical evidence on the impact of natural disaster risks on insurance take-up (Michel-Kerjan & Kousky 2010; Gallagher 2014). When observed alongside an earlier finding on the impact of cyclones on migration, this suggests different coping strategies are employed depending on the historical cyclone exposure of the locality: individuals in cyclone-prone areas are more likely to purchase insurance, while individuals in previously cyclone-free regions are more likely to migrate.

9. Dynamic impacts of cyclones on residential outcomes

Given that residential decisions involve forward planning and delayed adjustments (Nguyen *et al.*, 2024), we delve into the dynamic effects of cyclones on housing choices. To capture this dynamic, we introduce an additional variable in Equation (1) representing exposure to cyclones one year prior to the measured residential outcomes.[23] The estimates for both concurrent and lagged cyclone exposure are presented in Table 5. The results for simultaneous cyclone exposure largely echo the baseline findings in Table 2, reinforcing our earlier conclusions. Interestingly, most estimates of lagged cyclone exposure lack statistical significance,[24] suggesting that cyclones have an immediate impact on housing outcomes. This finding aligns with the notion that cyclones are typically regarded as "fast onset" events, exerting more

[23] While we refrain from including additional lags due to sample size limitations, the findings remain relatively robust even when controlling for cyclone exposure two years prior (results not shown).

[24] Exceptions are a few marginally statistically significant and positive estimates which indicate some differed cyclone impacts on housing outcomes. For instance, individuals living in a postcode within 100 km from any past cyclone's path are more likely ($p<0.1$, Panel B Column 5) to indicate a desire to relocate in the following survey wave. In the same vein, individuals residing within 30km of any category 5 cyclone in the previous year are 3 pp more likely ($p<0.1$, Panel C Column 2) to relocate in the following year.

immediate impacts compared to other "slow onset" events such as drought or temperature increases (Cattaneo *et al.* 2019).

However, some intriguing patterns emerge with statistically significant negative coefficients for lagged cyclone exposure, contrary to the concurrent effects. For instance, Table 5 (Panel A, Columns 5-7) reveals that individuals within 60 km of a past category 5 cyclone's eye or within 100 km of any previous year's cyclone are significantly ($p < 0.05$) less likely to report natural disaster-related home damage in the following year.

These seemingly contradictory findings, coupled with the results from the previous section, suggest a plausible coping mechanism. Specifically, households significantly increased their home and contents insurance purchases after experiencing a cyclone, and this acquired insurance acts as a shield, reducing repair costs after future cyclones. Therefore, the lower reported home damage among those facing a previous year's cyclone can be attributed to their proactive insurance purchases in response to the initial event. This acquired protection helps mitigate the impact of future cyclones, resulting in less reported damage (Hsiang & Narita 2012; Bakkensen & Mendelsohn 2016), highlighting the role of cyclone readiness.[25]

Furthermore, other statistically significant ($p < 0.05$) negative estimates of lagged cyclones on current migration further support the hypothesis that home insurance acquisition serves as a mitigating mechanism. Particularly, Table 5 reveals statistically significant negative estimates for lagged cyclone exposure on current relocation variables in Panel F, Column 3, and Panels D, E, and F, Column 5, indicating that individuals residing within 60 km or 100 km of a past cyclone are less likely to relocate to another LGA or state in the following year. These individuals who faced cyclones in the previous year might have fortified their existing homes

[25] In order to thoroughly examine the impacts of cyclone exposure on home damage, we conducted supplementary analyses investigating the effects of cyclones occurring 1, 2, 3, and 4 quarters preceding the interview date on quarterly natural disaster-related home damages. The quarterly findings (presented in Appendix B) closely align with the yearly results outlined in this section.

to prepare for future cyclones, leading to reduced likelihood of major home damage or relocation. This result, combined with one of our earlier findings showing that only uninsured individuals relocate in response to cyclones, provides further support for the hypothesis that home insurance acquisition acts as a mitigating mechanism.

Overall, the results broaden our understanding of insurance acquisition as an adaptation mechanism. Interestingly, insurance acquisition appears to only reduce subsequent relocation for those previously affected by less severe cyclones (within a 60 km radius of the eye). This is evidenced by statistically significant negative estimates of lagged cyclones on current relocation for this group. In contrast, our earlier finding, confirmed here, shows that relocation is more likely for individuals experiencing severe cyclones (within 30 km of the eye). These patterns suggest that cyclone-affected individuals might employ each coping strategy depending on cyclone severity.[26] They may choose relocation in response to severe cyclones that likely caused significant home damage. Conversely, individuals facing less severe cyclones may opt to strengthen existing homes, potentially aided by insurance claims, to increase future resilience.

10. Impacts of home damage on residential outcomes

This section investigates the direct impact of natural disaster related home damage on residential outcome R_{it}, using the following econometric model:

$$R_{it} = \rho + \sigma D_{it} + X_{it}\pi + \delta_i + \omega_{it} \qquad (2)$$

[26] Regrettably, constraints in data availability, such as uncertainty regarding the extent of home damage severity, absence of insurance claim records, and the relatively limited sample size, hinder our ability to arrive at a conclusive understanding of the intricate interplay between the two identified coping mechanisms. Nonetheless, in the subsequent section, we uncover corroborating evidence indicating that home damage resulting from less severe cyclones, defined by cyclones within 100 km from individuals' residential postcodes, does not elevate relocation rates (See Appendix Table A6).

where D_{it} is a binary variable capturing whether the individual's home was damaged or destroyed by a weather-related disaster. X_{it} and δ_i are described as in Equation (1). ω_{it} is an error term, and ρ, σ and π are vectors of parameters to be estimated.

In equation (2), σ is the parameter of interest, which captures the effect of home damage on the individual's residential responses. In this section, we consider all residential outcomes as described in Section 3.3, except the home damage variable which now acts as an explanatory variable. While the fixed-effects model controls for unobservable time-invariant individual characteristics, it cannot address potential endogeneity arising from time-varying factors simultaneously affecting home damage and migration decisions (Wooldridge 2010; Guiteras *et al.* 2015). Leveraging our finding of a significant impact of cyclone exposure on reported home damage, we employ exposure to any cyclone within 30 km from its eye as an instrument[27] to estimate the causal impact of home damage on residential choices in an individual Fixed-Effects Instrumental Variable (FE-IV) framework. Similar to the baseline analysis, we focus on states and territories impacted by at least one cyclone during the study period for estimation efficiency. However, the sample size for this analysis is reduced due to the availability of home damage data starting from wave 9 onwards.

Table 6 presents estimates of the home damage variable derived from both the FE and FE-IV models. The FE results (odd columns) reveal a positive and statistically significant association ($p < 0.05$) between home damage and all relocation outcomes except relocation intention. These correlations indicate that individuals reporting cyclone-induced home damage are significantly more inclined to relocate.

[27] Natural disasters have been employed to instrument for temporary shocks to local labour markets (Belasen & Polachek 2008), school displacement (Imberman *et al.* 2012), suppliers' output (Barrot & Sauvagnat 2016), changes in risk perception (Dessaint & Matray 2017), and uncertainty (Baker *et al.* 2023).

The FE-IV results (even columns) unveil two notable findings. Firstly, the first-stage F-statistic surpasses 200 in all regressions, robustly rejecting the null hypothesis of a weak instrument (Stock & Yogo 2005). Secondly, FE-IV estimates for the four actual mobility variables demonstrate significant changes in magnitude and significance compared to the FE results. Particularly noteworthy is the magnitude escalation of estimates, ranging from five-fold (for residential relocation) to 41-fold (for relocation distance). Moreover, the estimate of home damage on residential relocation loses statistical significance, while estimates on relocation distance and inter-LGA relocation become marginally less statistically significant at the 10% level. Conversely, the estimate on inter-state relocation gains greater statistical significance at $p < 0.01$.

FE-IV estimates, when statistically significant, reveal a substantially heightened impact of home damage on migration compared to FE estimates. For instance, the significant ($p<0.10$) FE-IV estimate suggests that individuals with home damage relocate approximately 448 kms further, contrasting with only an 11-km increase estimated by the FE model. Similarly, the FE-IV estimate indicates that cyclone-induced home damage amplifies the probability of relocating to other states by 29 pp, compared to just a one pp increase estimated by the FE model. This impact of home damage on inter-state residential mobility, as indicated by the FE-IV estimate, is substantial, representing approximately 7.54 times of the mean of 3.78% of individuals undertaking any inter-state relocation in our sample.

The aforementioned FE-IV results underscore that home damage resulting from natural disasters significantly heightens domestic migration, particularly long-distance relocation to other LGAs and states. Further FE-IV findings, presented in the bottom right section of Table 6, emphasize the pivotal role of cyclone-induced home damage in propelling domestic migration, as households experiencing such damage exhibit statistically insignificant changes in expenditures on home, content, and vehicle insurance - another coping mechanism previously identified. This finding is reinforced by recent research by Nguyen and Mitrou (2024), employing a dataset and empirical methodology similar to ours, revealing an insignificant impact of cyclones on health, another plausible catalyst for migration (Cattaneo *et al.* 2019).

In summary, the results from this section reveal that cyclone-induced home damage substantially elevates the probability of relocation, particularly over extended distances. Crucially, these results imply that disregarding the endogeneity of self-reported home damage leads to an underestimation of its genuine impact on migration decisions. They furnish empirical support for the hypothesis positing natural disaster home damage as a significant driver of disaster-induced migration. To our knowledge, this study offers novel and robust empirical insights into this underexplored phenomenon, thereby making a substantial contribution to the existing literature (Cattaneo *et al.* 2019; Kaczan & Orgill-Meyer 2020).

11. Conclusion

This study leverages the unique natural experiment of randomly timed exposure to local cyclones to conduct a comprehensive causal analysis of their impacts on residential outcomes in Australia. Our findings indicate that cyclones, especially those of higher severity and closer proximity, notably escalate reported home damage and impact relocation intentions and actual migration patterns, predominantly fuelling long-distance domestic migration. Additionally, these cyclones prompt individuals to acknowledge the significance of insurance and actively seek coverage. Furthermore, we reveal home insurance acquisition as another vital coping mechanism employed alongside migration, proving particularly effective in offsetting future repair costs.

In-depth heterogeneity analyses elucidate that the selection among these strategies is contingent upon cyclone severity alongside various individual, household, and locational attributes. In response to more severe cyclonic events, individuals may opt for either relocation or the purchase of home-related insurance. Furthermore, the study reveals specific demographic markers influencing individuals' reactions to cyclones. Notably, characteristics such as youth, tenancy, higher socioeconomic standing, lack of pre-existing insurance coverage, and residency in rural or coastal areas, as well as historically unaffected regions, correlate with an increased propensity for post-cyclone migration. Conversely, individuals characterized by attributes such as male gender, youth, homeownership, higher socioeconomic status, and residence in rural or inland areas, or historically cyclone-prone regions, are more inclined to pursue home insurance subsequent to cyclone impact. Our continued investigation into the dynamic effects of cyclones on residential outcomes uncovers that less severe cyclones may stimulate efforts to reinforce existing dwellings. Such initiatives could be facilitated by reimbursements from previously acquired insurance, aimed at bolstering future resilience.

Our findings hold important implications for policies and strategies aimed at mitigating the damaging impacts of future cyclones. They emphasize the need for targeted support and resilience-building strategies in vulnerable groups and regions. Recognizing this previously unidentified vulnerability requires reevaluating existing risk perception and adaptation frameworks. Policymakers should prioritize investing in disaster preparedness initiatives tailored separately to historically cyclone-free and cyclone-prone regions, focusing on enhancing public awareness and community resilience. Simultaneously, targeted socio-economic support might be crucial for assisting displaced individuals and facilitating their reintegration into new communities. Ultimately, incorporating this novel insight into policy planning can potentially empower communities to better withstand the disruptive forces of future cyclones.

This study offers a comprehensive analysis of residential responses to cyclones in Australia. However, it is important to acknowledge some limitations that offer opportunities for future research. First, while this study sheds light on the impact of cyclones on residential choices, it does not explore the full range of potential consequences. Future research using the rich HILDA data and similar empirical models could examine the effects of cyclones on other psychological and socio-economic outcomes. This would provide a more holistic understanding of the social and economic burden of cyclones.

Second, this study identifies migration and insurance acquisition as key coping mechanisms, but data limitations hinder a deeper exploration of their interaction. Future research employing more advanced data or models, such as dynamic or simultaneous modelling approaches, could provide more nuanced insights into how these strategies work together in response to cyclones. This would offer more valuable policy-relevant evidence to guide interventions that support individuals in navigating these difficult choices.

References

Baez, J., Caruso, G., Mueller, V., Niu, C., 2017. Droughts augment youth migration in Northern Latin America and the Caribbean. Climatic Change 140, 423-435

Baker, S.R., Bloom, N., Terry, S.J., 2023. Using Disasters to Estimate the Impact of Uncertainty. The Review of Economic Studies 91, 720-747

Bakkensen, L.A., Mendelsohn, R.O., 2016. Risk and Adaptation: Evidence from Global Hurricane Damages and Fatalities. Journal of the Association of Environmental and Resource Economists 3, 555-587

Barrios, S., Bertinelli, L., Strobl, E., 2006. Climatic change and rural–urban migration: The case of sub-Saharan Africa. Journal of Urban Economics 60, 357-371

Barrot, J.-N., Sauvagnat, J., 2016. Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks. The Quarterly Journal of Economics 131, 1543-1592

Baryshnikova, N.V., Pham, N.T., 2019. Natural disasters and mental health: A quantile approach. Economics letters 180, 62-66

Belasen, A.R., Polachek, S.W., 2008. How Hurricanes Affect Wages and Employment in Local Labor Markets. American Economic Review: Papers & Proceedings 98, 49-53

Beltrán, A., Maddison, D., Elliott, R., 2019. The impact of flooding on property prices: A repeat-sales approach. Journal of Environmental Economics and Management 95, 62-86

Bernstein, A., Struyven, D., 2022. Housing Lock: Dutch Evidence on the Impact of Negative Home Equity on Household Mobility. American Economic Journal: Economic Policy 14, 1-32

Black, R., Arnell, N.W., Adger, W.N., Thomas, D., Geddes, A., 2013. Migration, immobility and displacement outcomes following extreme events. Environmental Science & Policy 27, S32-S43

Black, R., Bennett, S.R.G., Thomas, S.M., Beddington, J.R., 2011. Migration as adaptation. Nature 478, 447-449

Bloze, G., Skak, M., 2016. Housing equity, residential mobility and commuting. Journal of Urban Economics 96, 156-165

Bohra-Mishra, P., Oppenheimer, M., Hsiang, S.M., 2014. Nonlinear permanent migration response to climatic variations but minimal response to disasters. Proceedings of the National Academy of Sciences 111, 9780-9785

BOM, 2024. Understanding cyclones. In: http://www.bom.gov.au/cyclone/tropical-cyclone-knowledge-centre/understanding Bureau of Meteorology (BOM) (Ed.)

Botzen, W.J.W., Deschenes, O., Sanders, M., 2019. The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. Review of Environmental Economics and Policy 13, 167-188

Boustan, L.P., Kahn, M.E., Rhode, P.W., 2012. Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century. American Economic Review: Papers & Proceedings 102, 238-44

Cameron, A.C., Miller, D.L., 2015. A Practitioner's Guide to Cluster-Robust Inference. Journal of Human Resources 50, 317-372

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., et al., 2022. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. The Quarterly Journal of Economics 137, 2037-2105

Carleton, T.A., Hsiang, S.M., 2016. Social and economic impacts of climate. Science 353, aad9837

Carroll, N., Frijters, P., Shields, M., 2009. Quantifying the costs of drought: new evidence from life satisfaction data. Journal of Population Economics 22, 445-461

Cattaneo, C., Beine, M., Fröhlich, C.J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., et al., 2019. Human Migration in the Era of Climate Change. Review of Environmental Economics and Policy 13, 189-206

Chort, I., de la Rupelle, M., 2022. Managing the impact of climate on migration: evidence from Mexico. Journal of Population Economics 35, 1777-1819

Currie, J., Rossin-Slater, M., 2013. Weathering the storm: Hurricanes and birth outcomes. Journal of Health Economics 32, 487-503

Dell, M., Jones, B.F., Olken, B.A., 2009. Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates. American Economic Review: Papers & Proceedings 99, 198-204

Dell, M., Jones, B.F., Olken, B.A., 2014. What Do We Learn from the Weather? The New Climate–Economy Literature. Journal of Economic Literature 52, 740-798

Deryugina, T., Kawano, L., Levitt, S., 2018. The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns. American Economic Journal: Applied Economics 10, 202-33

Deryugina, T., Marx, B.M., 2021. Is the Supply of Charitable Donations Fixed? Evidence from Deadly Tornadoes. American Economic Review: Insights 3, 383-98

Deschenes, O., Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. The American Economic Review, 354-385

Dessaint, O., Matray, A., 2017. Do managers overreact to salient risks? Evidence from hurricane strikes. Journal of Financial Economics 126, 97-121

Dillon, A., Mueller, V., Salau, S., 2011. Migratory Responses to Agricultural Risk in Northern Nigeria. American Journal of Agricultural Economics 93, 1048-1061

Elsner, J.B., Kossin, J.P., Jagger, T.H., 2008. The increasing intensity of the strongest tropical cyclones. Nature 455, 92-95

Falco, C., Galeotti, M., Olper, A., 2019. Climate change and migration: Is agriculture the main channel? Global Environmental Change 59, 101995

Franklin, S., Labonne, J., 2019. Economic Shocks and Labor Market Flexibility. Journal of Human Resources 54, 171-199

Fussell, E., Curran, S.R., Dunbar, M.D., Babb, M.A., Thompson, L., Meijer-Irons, J., 2017. Weather-Related Hazards and Population Change: A Study of Hurricanes and Tropical Storms in the United States, 1980–2012. The ANNALS of the American Academy of Political and Social Science 669, 146-167

Gallagher, J., 2014. Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. American Economic Journal: Applied Economics 6, 206-33

Groen, J.A., Kutzbach, M.J., Polivka, A.E., 2020. Storms and Jobs: The Effect of Hurricanes on Individuals' Employment and Earnings over the Long Term. Journal of Labor Economics 38, 653-685

Gröger, A., Zylberberg, Y., 2016. Internal labor migration as a shock-coping strategy: evidence from a typhoon. American Economic Journal: Applied Economics 8, 123-53

Guiteras, R., Jina, A., Mobarak, A.M., 2015. Satellites, Self-Reports, and Submersion: Exposure to Floods in Bangladesh. American Economic Review: Papers & Proceedings 105, 232-36

Gunby, N., Coupé, T., 2023. Weather-Related Home Damage and Subjective Well-Being. Environmental and Resource Economics 84, 409-438

Harris, J.R., Todaro, M.P., 1970. Migration, Unemployment and Development: A Two-Sector Analysis. The American Economic Review 60, 126

Hickson, J., Marshan, J., 2022. Labour Market Effects of Bushfires and Floods in Australia: A Gendered Perspective. Economic Record 98, 1-23

Hornbeck, R., 2012. The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe. American Economic Review 102, 1477-1507

Hsiang, S.M., Jina, A.S., 2014. The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. National Bureau of Economic Research Working Paper No 20352

Hsiang, S.M., Narita, D., 2012. Adaptation to cyclone risk: Evidence from the global cross-section. Climate Change Economics 3, 1-28

Imberman, S.A., Kugler, A.D., Sacerdote, B.I., 2012. Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees. The American Economic Review 102, 2048-2082

Jessoe, K., Manning, D., Taylor, E.J., 2018. Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather. The Economic Journal 128, 230–261

Johar, M., Johnston, D.W., Shields, M.A., Siminski, P., Stavrunova, O., 2022. The economic impacts of direct natural disaster exposure. Journal of Economic Behavior & Organization 196, 26-39

Johnston, D.W., Önder, Y.K., Rahman, M.H., Ulubaşoğlu, M.A., 2021. Evaluating wildfire exposure: Using wellbeing data to estimate and value the impacts of wildfire. Journal of Economic Behavior & Organization 192, 782-798

Kaczan, D.J., Orgill-Meyer, J., 2020. The impact of climate change on migration: a synthesis of recent empirical insights. Climatic Change 158, 281-300

Kousky, C., 2019. The Role of Natural Disaster Insurance in Recovery and Risk Reduction. Annual Review of Resource Economics 11, 399-418

Kraehnert, K., Osberghaus, D., Hott, C., Habtemariam, L.T., Wätzold, F., Hecker, L.P., et al., 2021. Insurance against extreme weather events: An overview. Review of Economics 72, 71-95

Ladds, M., Keating, A., Handmer, J., Magee, L., 2017. How much do disasters cost? A comparison of disaster cost estimates in Australia. International Journal of Disaster Risk Reduction 21, 419-429

Logan, J.R., Issar, S., Xu, Z., 2016. Trapped in Place? Segmented Resilience to Hurricanes in the Gulf Coast, 1970–2005. Demography 53, 1511-1534

Magnusson, L.M., Roth, S., 2023. Distrustful Men and Risk-Averse Women: Evidence from the Black Saturday Fires in Victoria, Australia. Available at httpdx.doi.SSRN-id4371972

Mahajan, P., Yang, D., 2020. Taken by storm: Hurricanes, migrant networks, and US immigration. American Economic Journal: Applied Economics 12, 250-277

Marchiori, L., Maystadt, J.-F., Schumacher, I., 2012. The impact of weather anomalies on migration in sub-Saharan Africa. Journal of Environmental Economics and Management 63, 355-374

McIntosh, M.F., 2008. Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas. The American Economic Review: Papers and Proceedings 98, 54-57

Michel-Kerjan, E.O., Kousky, C., 2010. Come Rain or Shine: Evidence on Flood Insurance Purchases in Florida. Journal of Risk and Insurance 77, 369-397

Mitrou, F., Nguyen, H.T., Le, H.T., Zubrick, S.R., 2024. The causal impact of mental health on tobacco and alcohol consumption: an instrumental variables approach. Empirical Economics 66, 1287-1310

Mueller, V., Gray, C., Kosec, K., 2014. Heat stress increases long-term human migration in rural Pakistan. Nature Climate Change 4, 182-185

Nguyen, H.T., Duncan, A., 2017. Exchange rate fluctuations and immigrants' labour market outcomes: New evidence from Australian household panel data. Journal of International Economics 105, 174-186

Nguyen, H.T., Le, H.T., Connelly, L.B., 2021. Weather and children's time allocation. Health Economics 30, 1559-1579

Nguyen, H.T., Mitrou, F., 2024. In the eye of the storm: Quantifying the cascading impacts of cyclones. In: Paper presented at seminars at Monash University and The University of Melbourne in 03/2014

Nguyen, H.T., Mitrou, F., Zubrick, S., 2024. Retirement, housing mobility, downsizing and neighbourhood quality - A causal investigation. Journal of Housing Economics 63, 101977

Ouattara, B., Strobl, E., 2014. Hurricane strikes and local migration in US coastal counties. Economics Letters 124, 17-20

Pajaron, M.C., Vasquez, G.N.A., 2020. Weathering the storm: weather shocks and international labor migration from the Philippines. Journal of Population Economics 33, 1419-1461

Sheldon, T.L., Zhan, C., 2022. The impact of hurricanes and floods on domestic migration. Journal of Environmental Economics and Management 115, 102726

Smith, V.K., Carbone, J.C., Pope, J.C., Hallstrom, D.G., Darden, M.E., 2006. Adjusting to natural disasters. Journal of Risk and Uncertainty 33, 37-54

Spencer, N., Urquhart, M.-A., 2018. Hurricane Strikes and Migration: Evidence from Storms in Central America and the Caribbean. Weather, Climate, and Society 10, 569-577

Stock, J.H., Yogo, M., 2005. Testing for Weak Instruments in Linear IV Regression. In: Andrews DWK (ed.) Identification and Inference for Econometric Models. Identification and Inference for Econometric Models. Cambridge University Press, New York, pp. 80-108.

Summerfield, M., Garrard, B., Kamath, R., Macalalad, N., Nesa, M.K., Watson, N., et al., 2023. HILDA User Manual – Release 22. Melbourne Institute of Applied Economic and Social Research, The University of Melbourne

Thiede, B.C., Gray, C.L., 2017. Heterogeneous climate effects on human migration in Indonesia. Population and Environment 39, 147-172

Ulubaşoğlu, M.A., Rahman, M.H., Önder, Y.K., Chen, Y., Rajabifard, A., 2019. Floods, Bushfires and Sectoral Economic Output in Australia, 1978–2014. Economic Record 95, 58-80

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, Mass.

Zander, K.K., Wilson, T., Garnett, S.T., 2020. Understanding the role of natural hazards in internal labour mobility in Australia. Weather and Climate Extremes 29, 100261

Table 1: Sample means of key covariates and outcomes by cyclone exposure

	Affected by any cyclone	Unaffected	Affected - Unaffected (1) - (2)
	(1)	(2)	(3)
Age (years)	44.108	44.848	-0.741***
Married/De facto [(a)]	0.630	0.625	0.005
Separated/divorced/widowed [(a)]	0.132	0.140	-0.008**
Year 12 [(a)]	0.158	0.152	0.007*
Vocational or Training qualification [(a)]	0.402	0.355	0.047***
Bachelor or higher [(a)]	0.168	0.180	-0.012***
Household size	2.849	2.884	-0.036**
Major city [(a)]	0.344	0.611	-0.267***
Local area unemployment rate (%)	4.994	5.162	-0.168***
Local area SEIFA index	5.147	5.460	-0.313***
Natural disaster related home damage [(a)]	0.039	0.020	0.019***
Likely to relocate [(a)]	0.181	0.156	0.025***
Residential relocation [(a)]	0.214	0.182	0.032***
Relocation distance (km)	91.868	30.639	61.229***
Inter-LGA relocation [(a)]	0.120	0.104	0.016***
Inter-state relocation [(a)]	0.063	0.045	0.018***
Observations	8,601	196,000	

Notes: Figures are sample means. Estimated sample from the regression of the relocation intention as an outcome. [(a)] indicates a binary variable. Tests are performed on the significance of the difference between the sample mean for "affected" individuals (identified as those living in a postcode affected by any cyclone within 100 km from the cyclone eye) and "unaffected" individuals (remaining individuals). The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2: The concurrent impacts of cyclone exposures on residential outcomes

Distance to cyclone eye:	Within 30 km		Within 60 km		Within 100 km	
Cyclone category:	Any	Cat 5	Any	Cat 5	Any	Cat 5
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Natural disaster related home damage [(a)] (Observations: 126,326; Persons: 16,613; Mean: 2.07)					
Estimate	6.07***	17.32***	3.31***	11.85***	1.86***	7.48***
	[0.73]	[2.02]	[0.36]	[1.40]	[0.24]	[1.00]
Panel B:	Likely to relocate [(a)] (Observations: 204,466; Persons: 21,815; Mean: 15.68)					
Estimate	0.71	4.86***	0.93	3.49**	1.49***	3.34***
	[0.96]	[1.86]	[0.59]	[1.43]	[0.45]	[1.15]
Panel C:	Residential relocation [(a)] (Observations: 193,588; Persons: 20,805; Mean: 18.39)					
Estimate	1.76*	1.09	-0.24	2.33*	-0.51	0.83
	[1.01]	[1.82]	[0.60]	[1.40]	[0.47]	[1.16]
Panel D:	Relocation distance (Observations: 187,564; Persons: 19,119; Mean: 33.31)					
Estimate	30.69**	52.92*	1.12	32.58	7.59	19.45
	[13.39]	[30.23]	[6.87]	[20.82]	[4.69]	[15.25]
Panel E:	Inter-LGA relocation [(a)] (Observations: 193,588; Persons: 20,805; Mean: 10.50)					
Estimate	2.34***	1.43	0.12	0.87	-0.22	0.49
	[0.85]	[1.52]	[0.50]	[1.15]	[0.38]	[0.94]
Panel F:	Inter-state relocation [(a)] (Observations: 193,588; Persons: 20,805; Mean: 4.54)					
Estimate	1.64***	2.12*	-0.02	1.19	0.32	0.96
	[0.62]	[1.26]	[0.34]	[0.91]	[0.25]	[0.70]

Notes: Results reported in each column and panel are from a separate FE regression. "Observations", "Persons", and "Mean" refer to "Number of observations", "Number of unique individuals", and "Mean of the dependent variable", respectively. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. For all binary outcome variables, indicated with [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: The impacts of cyclone exposures on insurance belief and action

Distance to cyclone eye:	Within 30 km		Within 60 km		Within 100 km	
Cyclone category:	Any	Cat 5	Any	Cat 5	Any	Cat 5
	(1)	(4)	(5)	(8)	(9)	(12)
Panel A:	Having home contents insurance is essential [(a)] (Observations: 28544; Persons: 12801; Mean: 59.27)					
Current cyclone	4.07	4.95	6.45***	8.15***	5.10***	8.29***
	[3.29]	[4.11]	[2.46]	[2.80]	[1.97]	[2.48]
Lagged cyclone	-2.62		-1.36		-1.44*	
	[1.99]		[1.09]		[0.84]	
Panel B:	Has home contents insurance [(a)] (Observations: 28634; Persons: 12789; Mean: 74.99)					
Current cyclone	1.49	2.30	0.73	1.58	3.12**	2.90
	[2.20]	[2.97]	[1.65]	[2.04]	[1.44]	[1.80]
Lagged cyclone	1.96		1.18		0.17	
	[1.32]		[0.73]		[0.58]	
Panel C:	Having comprehensive motor vehicle insurance is essential [(a)] (Observations: 28600; Persons: 12814; Mean: 53.2)					
Current cyclone	4.12	12.59***	2.86	6.76**	5.03***	6.55**
	[3.47]	[3.85]	[2.57]	[2.85]	[1.94]	[2.57]
Lagged cyclone	-5.25**		-0.17		-0.38	
	[2.19]		[1.17]		[0.90]	
Panel D:	Has comprehensive motor vehicle insurance [(a)] (Observations: 26983; Persons: 12260; Mean: 90.02)					
Current cyclone	5.65***	4.50*	1.97	2.03	2.71**	3.20*
	[2.04]	[2.59]	[1.64]	[1.94]	[1.24]	[1.73]
Lagged cyclone	-0.12		0.73		0.22	
	[1.20]		[0.66]		[0.49]	
Panel E:	Annual household expenditure on other insurance such as home, contents, motor vehicle ($1,000) (Observations: 131634; Persons: 15712; Mean: 1.81)					
Current cyclone	-0.04	0.09	-0.03	0.12**	-0.01	0.12***
	[0.04]	[0.07]	[0.03]	[0.06]	[0.02]	[0.04]
Lagged cyclone	0.09**	0.25***	-0.03	0.19***	-0.04*	0.18***
	[0.04]	[0.09]	[0.03]	[0.07]	[0.02]	[0.05]
Panel F:	Annual household expenditure on other insurance such as home, contents, motor vehicle ≥ $1,250 [(a)] (Observations: 131634; Persons: 15712; Mean: 51.36)					
Current cyclone	-0.81	5.06**	-0.10	4.41***	0.56	4.89***
	[1.09]	[2.08]	[0.69]	[1.62]	[0.56]	[1.29]
Lagged cyclone	2.02*	1.46	-0.48	1.06	0.42	2.68**
	[1.09]	[1.90]	[0.70]	[1.51]	[0.56]	[1.25]

Notes: Results reported in each column and panel are from a separate FE specification like Equation (1) with a one-year lagged cyclone exposure variable as an additional explanatory variable. "Observations", "Persons", and "Mean" refer to "Number of observations", "Number of unique individuals", and "Mean of the dependent variable", respectively. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. For all binary outcome variables, indicated with [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Cyclone exposure, home related expenditure and role of insurance

Distance to cyclone eye:	Within 30 km		Within 60 km		Within 100 km	
Cyclone category:	Any	Cat 5	Any	Cat 5	Any	Cat 5
	(1)	(2)	(3)	(4)	(5)	(6)
Current cyclone	-0.63**	-0.43	-0.02	-0.59	0.11	-0.34
	[0.27]	[0.52]	[0.23]	[0.45]	[0.16]	[0.32]
Lagged insurance status	0.39***	0.38***	0.38***	0.38***	0.39***	0.38***
	[0.13]	[0.13]	[0.14]	[0.13]	[0.14]	[0.13]
Interaction between current cyclone and lagged insurance status	-1.38***	-1.68**	-0.29	-0.98	-0.27	-1.07**
	[0.45]	[0.84]	[0.60]	[0.65]	[0.42]	[0.47]
Observations	116,248	116,248	116,248	116,248	116,248	116,248
Number of unique persons	14,810	14,810	14,810	14,810	14,810	14,810
Mean of dep. variable	3.21	3.21	3.21	3.21	3.21	3.21
Proportion affected by current cyclone (%)	1.03	0.26	2.97	0.44	5.16	0.65

Notes: Results reported in each column are from a separate FE equation (1), with a one-year lagged insurance status and its interaction with the current cyclone exposure variable as two additional control variables. "Lagged insurance status" is a dummy variable taking the value of one if the household spent $1,250 or more annually on combined home, contents, and motor vehicle insurance (adjusted to 2010 prices) and zero otherwise. Dependent variable: Annual household expenditure on home repairs/renovations ($1,000). Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: The dynamic impacts of cyclone exposure on residential outcomes

Distance to cyclone eye:	Within 30 km		Within 60 km		Within 100 km	
Cyclone category:	Any	Cat 5	Any	Cat 5	Any	Cat 5
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Natural disaster related home damage [(a)] (Observations: 116,898; Persons: 14,815; Mean: 2.02)					
Current cyclone	6.04***	17.27***	3.26***	11.63***	1.87***	7.31***
	[0.75]	[2.09]	[0.37]	[1.43]	[0.25]	[1.03]
Lagged cyclone	0.85	0.05	0.21	-1.67**	-0.92***	-2.33***
	[0.56]	[1.08]	[0.28]	[0.77]	[0.21]	[0.54]
Panel B:	Likely to relocate [(a)] (Observations: 179,271; Persons: 18,062; Mean: 14.81)					
Current cyclone	1.52	6.07***	1.08*	3.83**	1.52***	3.78***
	[1.00]	[1.96]	[0.61]	[1.52]	[0.47]	[1.23]
Lagged cyclone	0.76	-0.12	0.08	0.57	0.87*	0.60
	[1.00]	[1.83]	[0.59]	[1.38]	[0.46]	[1.12]
Panel C:	Residential relocation [(a)] (Observations: 179,315; Persons: 18,065; Mean: 16.51)					
Current cyclone	1.65	0.85	-0.42	1.98	-0.59	0.55
	[1.02]	[1.89]	[0.61]	[1.48]	[0.48]	[1.21]
Lagged cyclone	0.17	3.39*	-0.29	-0.42	-0.68	0.01
	[1.05]	[2.05]	[0.64]	[1.55]	[0.49]	[1.25]
Panel D:	Relocation distance (Observations: 179,270; Persons: 18,065; Mean: 32.57)					
Current cyclone	31.79**	60.83**	0.33	32.92	7.30	20.65
	[13.60]	[31.02]	[7.10]	[21.22]	[4.88]	[15.57]
Lagged cyclone	-1.25	46.09	-8.97	2.84	-12.77**	4.71
	[13.80]	[32.01]	[7.46]	[21.09]	[5.27]	[15.12]
Panel E:	Inter-LGA relocation [(a)] (Observations: 179,315; Persons: 18,065; Mean: 7.99)					
Current cyclone	1.97**	0.89	0.01	0.31	-0.40	-0.08
	[0.81]	[1.48]	[0.48]	[1.11]	[0.36]	[0.91]
Lagged cyclone	0.70	2.70	-0.49	-0.28	-0.75**	0.44
	[0.86]	[1.66]	[0.49]	[1.16]	[0.37]	[0.94]
Panel F:	Inter-state relocation [(a)] (Observations: 179,315; Persons: 18,065; Mean: 1.56)					
Current cyclone	1.14**	1.24	-0.27	0.33	0.08	-0.01
	[0.50]	[1.06]	[0.26]	[0.75]	[0.19]	[0.54]
Lagged cyclone	-0.42	0.39	-0.86***	-0.96	-0.81***	-0.35
	[0.49]	[1.09]	[0.28]	[0.74]	[0.20]	[0.55]

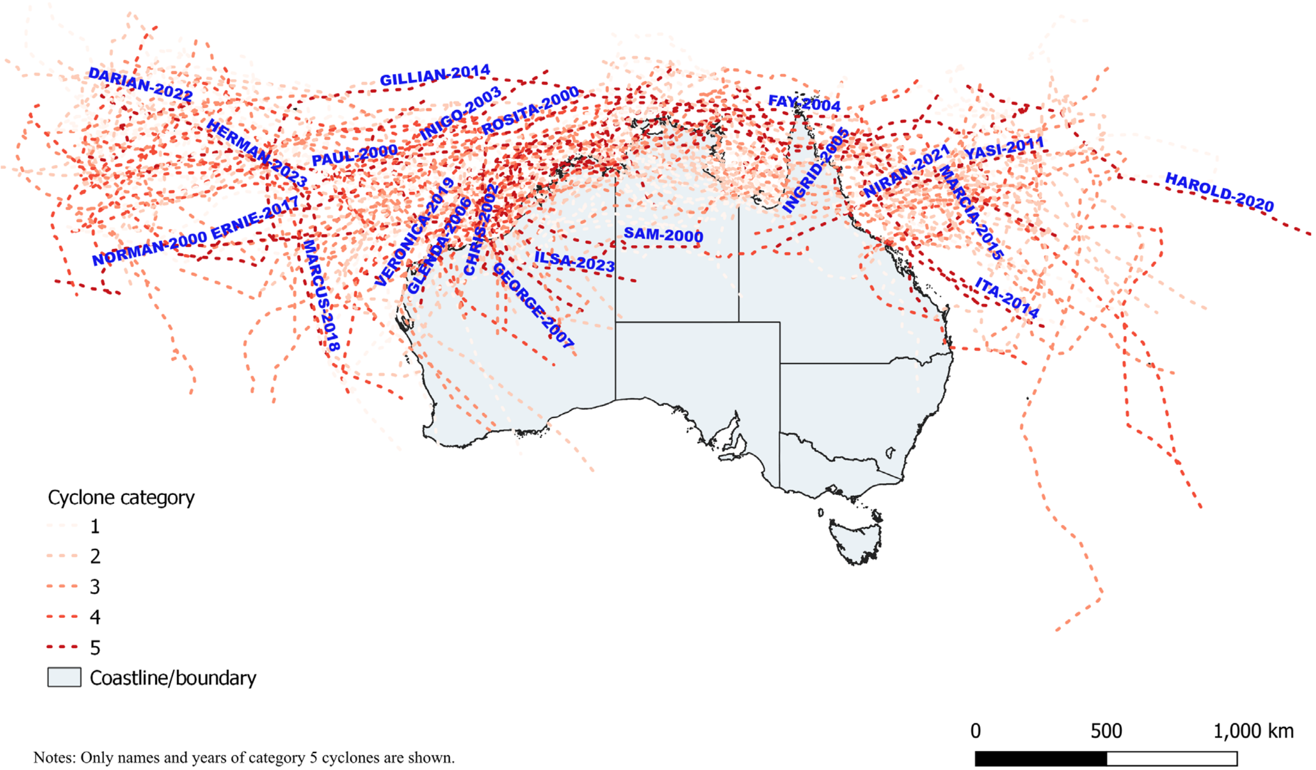
Notes: Results reported in each column and panel are from a separate FE regression. "Observations", "Persons", and "Mean" refer to "Number of observations", "Number of unique individuals", and "Mean of the dependent variable", respectively. For all binary outcome variables, indicated with [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6: Impact of cyclone induced home damage on migration and home insurance

Estimator:	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Housing outcome:	Likely to relocate [a]		Residential relocation [a]		Relocation distance (km)		Inter-LGA relocation [a]	
Current home damage	-0.01	-0.12	4.75***	21.65	10.92**	447.77*	2.30***	25.95*
	[0.02]	[0.57]	[0.84]	[17.88]	[4.75]	[231.16]	[0.67]	[14.49]
Observations	123,939		121,934		119,307		121,934	
Number of unique persons	14,241		14,129		13,768		14,129	
Mean of dep. variable	1.91		16.92		29.96		9.39	
F statistic		219.75		218.15		209.88		218.15
Housing outcome:	Inter-state relocation [a]				Annual household expenditure on home, contents, motor vehicle insurance ($1,000)		Annual household expenditure on other insurance such as home, contents, motor vehicle ≥ $1,250 [a]	
Current home damage	0.96**	28.51***			0.05*	-0.74	0.45	-16.15
	[0.40]	[10.66]			[0.03]	[0.53]	[0.84]	[17.73]
Observations	121,934				116,330		116,330	
Number of unique persons	14,129				13,845		13,845	
Mean of dep. variable	3.78				1.64		51.28	
F statistic		218.15				206.4		206.4

Notes: FE results are from the regression (2) while FE-IV results from regressions (1) and (2). "F-statistic" denotes the F statistic for the strength of the excluded instrument in the first stage regression. Instrument: Any cyclone within 30 km from its eye. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. For all binary outcome variables, indicated with [a], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Robust standard errors clustered at the individual level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

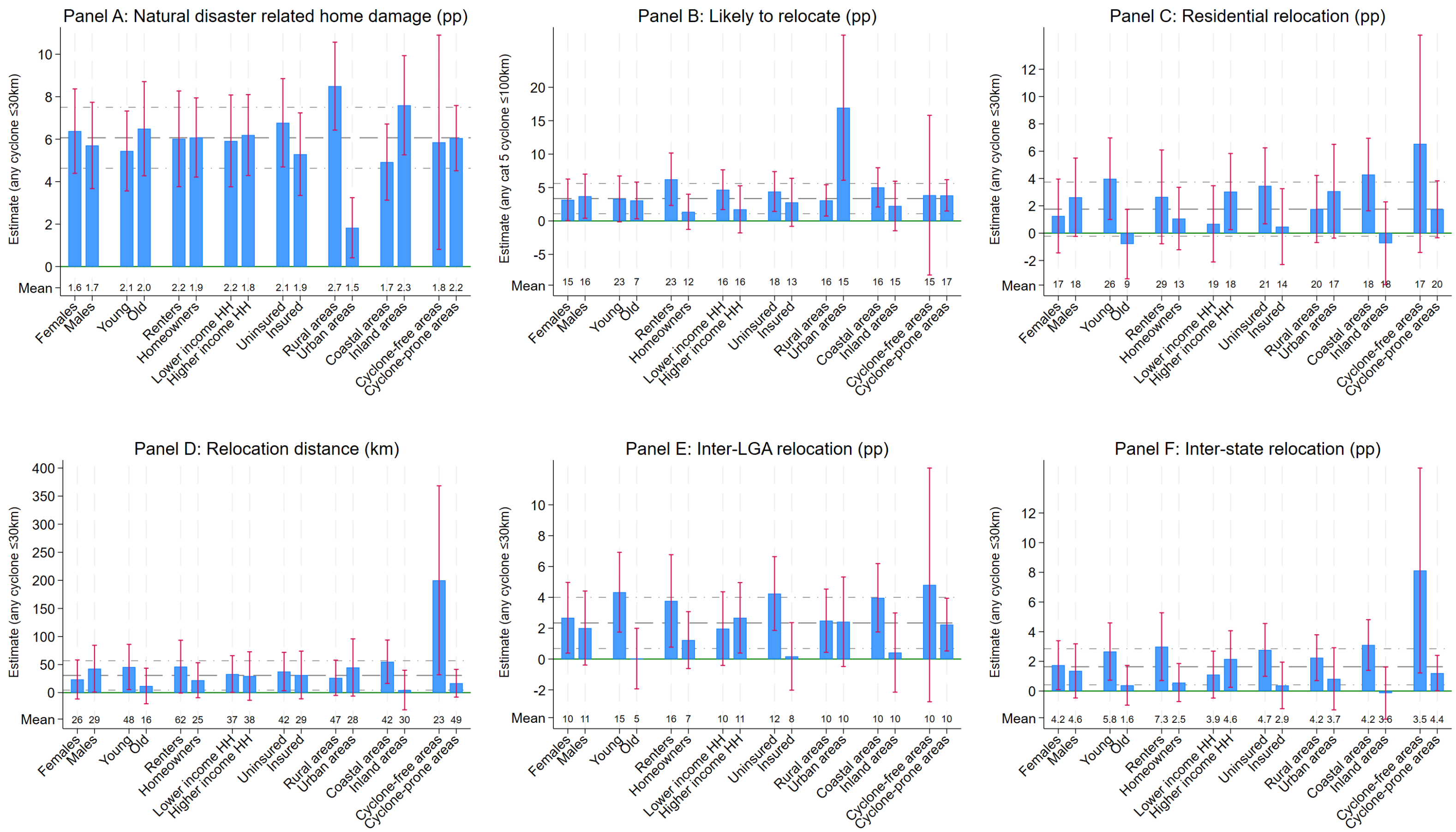
Figure 1: Tropical cyclone hit map between 2000 and 2023



Notes: Only names and years of category 5 cyclones are shown.

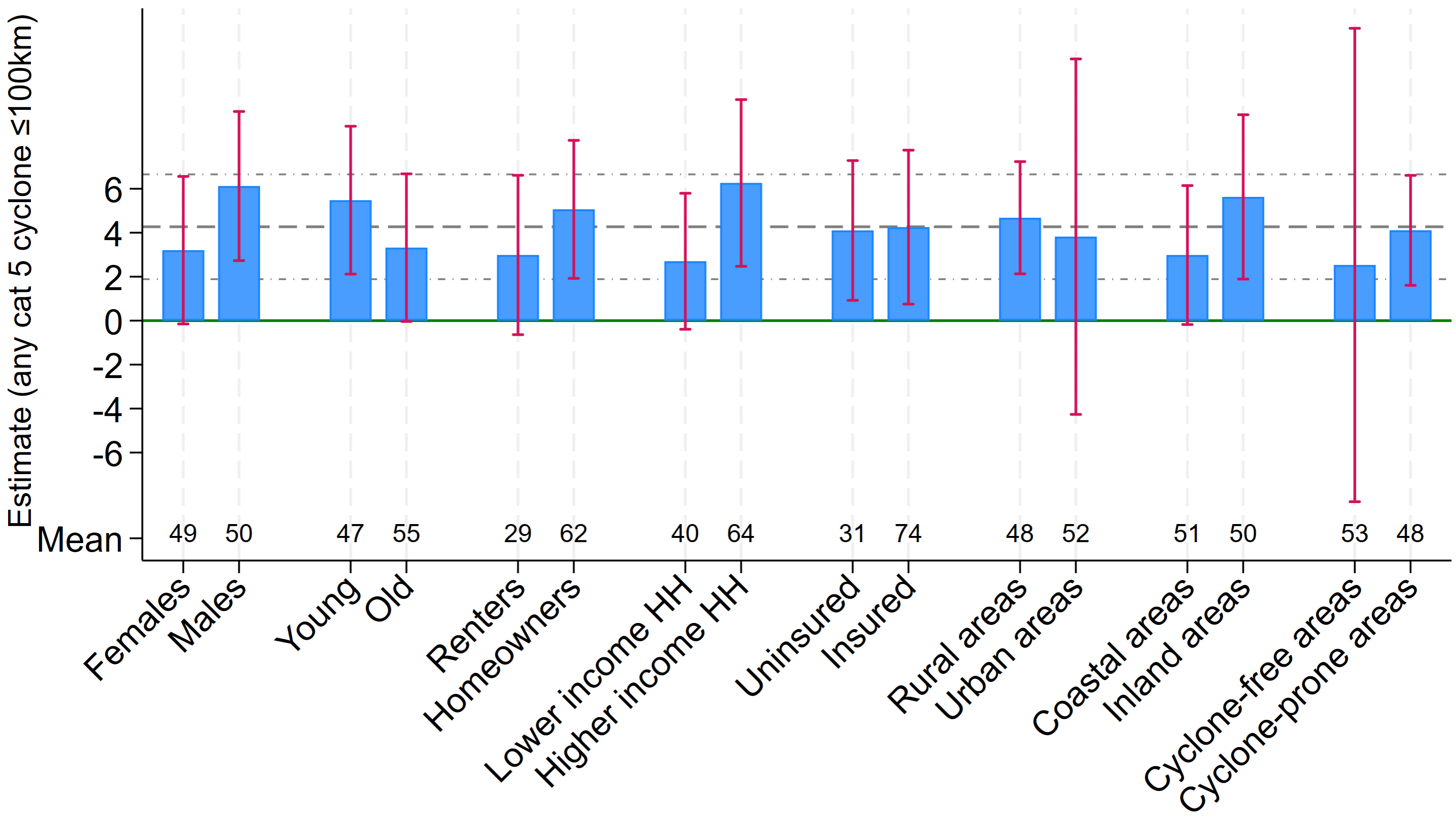
Notes: Cyclone category is classified using the maximum mean wind speed cut-offs from BOM. Cyclones are available up to November 2023.

Figure 2: Heterogeneity in the cyclone impact on housing outcomes



Notes: Results for different sub-populations are obtained from a separate FE regression. For all binary outcome variables, sample mean, coefficient estimate and its 95% confidence intervals are multiplied by 100 for aesthetic purposes. The dash (short dash dot) horizontal line shows the cyclone exposure coefficient (95% confidence interval) estimates for the whole population. "pp" denotes percentage points. "Mean" indicates the mean of the respective dependent variable for each sub-population printed below the bars. Detailed regression results are reported in Appendix Table A4.

Figure 3: Heterogeneity in the cyclone impact on home and content insurance purchase



Notes: Results for different sub-populations are obtained from a separate FE regression. The dependent variable is a binary one, taking the value of one if the household spent \$1,250 or more annually on combined home, contents, and motor vehicle insurance (adjusted to 2010 prices) and zero otherwise. Sample mean, coefficient estimate and its 95% confidence intervals are multiplied by 100 for aesthetic purposes. The dash (short dash dot) horizontal line shows the cyclone exposure coefficient (95% confidence interval) estimates for the whole population. "Mean" indicates the mean of the respective dependent variable for each sub-population printed below the bars. Detailed regression results are reported in Appendix Table A5.

Online Appendix

for refereeing purposes and to be published online

Appendix A reports additional results.

Appendix B reports results on impact of quarterly cyclone exposure on home damage.

Appendix Table A1: Variable description and summary statistics

Variable	Description	Mean	Min	Max	Standard deviations		
					Overall	Between	Within
Age (years)	The respondent's age at the survey time (years)	44.82	14.00	101.00	18.85	19.15	4.93
Married/De facto	Dummy variable: = 1 if the individual is married or in de factor relationship at the survey time and zero otherwise	0.63	0.00	1.00	0.48	0.45	0.25
Separated/divorced/widowed	Dummy variable: = 1 if the individual is separated/divorced/widowed at the survey time and zero otherwise	0.14	0.00	1.00	0.35	0.30	0.16
Year 12	Dummy: = 1 if the individual completes Year 12 and zero otherwise	0.15	0.00	1.00	0.36	0.34	0.17
Vocational or Training qualification	Dummy: = 1 if the individual has a vocational or training qualification and zero otherwise	0.36	0.00	1.00	0.48	0.45	0.16
Bachelor or higher	Dummy: = 1 if the individual has a bachelor degree or higher and zero otherwise	0.18	0.00	1.00	0.38	0.35	0.13
Household size	Number of household members	2.88	1.00	17.00	1.49	1.38	0.85
Major city	Dummy variable: = 1 if the individual lives in a major city and zero otherwise	0.60	0.00	1.00	0.49	0.47	0.18
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	5.15	2.10	8.10	1.16	0.83	1.02
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area	5.45	1.00	10.00	2.88	2.68	1.24

Notes: Estimated sample of 204,466 observations from the regression of the relocation intention as an outcome.

Appendix Table A1: Variable description and summary statistics (continued)

Variable	Description	Mean	Min	Max	Standard deviations			Count of individuals affected
					Overall	Between	Within	
Natural disaster related home damage	Dummy variable: = 1 if home destroyed due to a weather-related disaster last year and zero otherwise	0.02	0.00	1.00	0.14	0.10	0.13	
Likely to relocate	Dummy variable: = 1 if responses "Likely" or "Very likely" to a question asking "How likely is it that you will move in the next 12 months?", and zero otherwise	0.16	0.00	1.00	0.36	0.29	0.31	
Residential relocation	Dummy variable: = 1 if move address since last survey wave and zero otherwise	0.18	0.00	1.00	0.39	0.31	0.33	
Relocation distance	Great circle distance between the previous and current geocoded addresses (km)	33.31	0.00	3946.00	245.57	225.92	214.87	
Inter-LGA relocation	Dummy variable: = 1 if move address between Local Government Area (LGA) since last survey wave and zero otherwise	0.10	0.00	1.00	0.31	0.30	0.26	
Inter-state relocation	Dummy variable: = 1 if move address between states/territories since last survey wave and zero otherwise	0.05	0.00	1.00	0.21	0.29	0.17	
Any cyclone within 30 km	Dummy variable: = 1 if an individual's residential postcode was within 30 km of any cyclone's eye last year and zero otherwise	0.009	0.00	1.00	0.09	0.06	0.08	1,763
Any category 5 cyclone within 30 km	Dummy variable: = 1 if an individual's residential postcode was within 30 km of any category 5 cyclone's eye last year and zero otherwise	0.002	0.00	1.00	0.05	0.02	0.05	487
Any cyclone within 60 km	Dummy variable: = 1 if an individual's residential postcode was within 60 km of any cyclone's eye last year and zero otherwise	0.024	0.00	1.00	0.15	0.09	0.14	4,948
Any category 5 cyclone within 60 km	Dummy variable: = 1 if an individual's residential postcode was within 60 km of any category 5 cyclone's eye last year and zero otherwise	0.004	0.00	1.00	0.06	0.03	0.06	818
Any cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any cyclone's eye last year and zero otherwise	0.042	0.00	1.00	0.20	0.12	0.18	8,601
Any category 5 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 5 cyclone's eye last year and zero otherwise	0.006	0.00	1.00	0.08	0.04	0.07	1,198

Notes: Estimated sample of 204,466 observations from the regression of the relocation intention as an outcome.

Appendix Table A2: Determinants of sample attrition

Dependent variable:	Attrition due to any reason	Attrition due to being overseas
	(1)	(2)
Any cyclone within 30 km	0.43	0.01
	[0.61]	[0.18]
Lagged any cyclone within 30 km	-0.99*	0.02
	[0.59]	[0.13]
Age	-3.36***	-0.45
	[1.25]	[0.34]
Age squared	0.01***	-0.00**
	[0.00]	[0.00]
Married/De facto [(a)]	0.18	-0.67***
	[0.35]	[0.12]
Separated/divorced/widowed [(a)]	0.12	-0.73***
	[0.49]	[0.15]
Year 12 [(b)]	5.40***	0.46***
	[0.43]	[0.15]
Vocational or Training qualification [(b)]	4.68***	0.61***
	[0.48]	[0.14]
Bachelor or higher [(b)]	6.03***	1.35***
	[0.58]	[0.27]
Household size	0.03	-0.10***
	[0.07]	[0.03]
Major city	0.38	0.02
	[0.32]	[0.11]
Local area unemployment rate	-0.14	-0.02
	[0.09]	[0.02]
Local area SEIFA decile	0.00	0.02
	[0.05]	[0.02]
Observations	170,247	170,247
Number of unique persons	17,704	17,704
Mean of dependent variable (%)	6.25	0.50
R squared	0.02	0.00
P value (Wald test)	0.20	0.98
Proportion affected by current cyclone (%)	0.85	0.85
Proportion affected by lagged cyclone (%)	0.82	0.82

Notes: Results reported in each column are from a separate FE specification like Equation (1) with a one-year lagged cyclone exposure variable as an additional explanatory variable. [(a)] and [(b)] indicates "under Year 12 education" and "Single" as the comparison group, respectively. Other explanatory variables include state/territory dummies, year dummies, and survey month dummies. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Robust standard errors clustered at the individual level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A3: Robustness checks

	Natural disaster related home damage [(a)]	Likely to relocate [(a)]	Residential relocation [(a)]	Relocation distance (km)	Inter-LGA relocation [(a)]	Inter-state relocation [(a)]
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline						
Any cyclone within 30 km	6.07***	0.71	1.76*	30.69**	2.34***	1.64***
	[0.73]	[0.96]	[1.01]	[13.39]	[0.85]	[0.62]
Observations	126,326	204,466	193,588	187,564	193,588	193,588
Number of unique persons	16,613	21,815	20,805	19,119	20,805	20,805
Mean of dep. variable	2.07	15.68	18.39	33.31	10.5	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel B1: Different sample - Including only local government areas with at least one cyclone within 100 km						
Estimate	6.31***	0.68	1.78	12.62	1.94**	1.35**
	[0.84]	[1.05]	[1.11]	[12.99]	[0.91]	[0.67]
Observations	46,018	72,310	68,826	66,442	68,826	68,826
Number of unique persons	6,550	8,547	8,209	7,494	8,209	8,209
Mean of dep. variable	2.65	17.67	21.69	49.25	11.28	5.64
Proportion affected (%)	2.86	2.20	2.20	2.19	2.20	2.20
Panel B2: Different sample - Using a sample of all individuals observed in the data						
Any cyclone within 30 km	6.07***	0.49	1.91*	32.71**	2.35***	1.56**
	[0.73]	[0.96]	[1.00]	[13.75]	[0.84]	[0.62]
Observations	208,598	337,421	319,528	309,367	319,528	319,528
Number of unique persons	26,469	34,507	32,938	30,166	32,938	32,938
Mean of dep. variable	1.66	15.33	17.58	27.52	10.33	4.42
Proportion affected (%)	0.71	0.52	0.53	0.52	0.53	0.53
Panel C1: Different specification - Including postcode dummies						
Any cyclone within 30 km	6.07***	0.64	2.06**	22.50*	2.34***	1.64***
	[0.73]	[0.95]	[1.00]	[12.70]	[0.83]	[0.62]
Observations	126,295	204,418	193,540	187,516	193,540	193,540
Number of unique persons	16,613	21,815	20,804	19,117	20,804	20,804
Mean of dep. variable	2.07	15.68	18.38	33.27	10.49	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel C2: Different specification - Clustering at the postcode level						
Any cyclone within 30 km	6.05***	0.73	1.81	30.77*	2.36**	1.64*
	[1.87]	[1.14]	[1.31]	[15.90]	[1.16]	[0.85]
Observations	126,295	204,418	193,540	187,516	193,540	193,540
Number of unique persons	16,613	21,815	20,804	19,117	20,804	20,804
Mean of dep. variable	2.07	15.68	18.38	33.27	10.49	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87

Notes: The results presented in each column and panel are based on separate fixed-effects (FE) regressions, unless otherwise specified. Unless stated otherwise, other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level, unless indicated otherwise, in squared brackets. "Proportion affected" indicates the proportion of individuals affected by the respective cyclone exposure measure. For all binary outcome variables, denoted by [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A3: Robustness checks (continued)

	Natural disaster related home damage [(a)]	Likely to relocate [(a)]	Residential relocation [(a)]	Relocation distance (km)	Inter-LGA relocation [(a)]	Inter-state relocation [(a)]
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C3: Different specification - Employing a pooled OLS regression model without controlling for individual FE						
Any cyclone within 30 km	5.96***	1.09	2.16**	40.02***	2.26***	1.47**
	[0.72]	[0.97]	[1.05]	[14.61]	[0.88]	[0.67]
Observations	126,326	204,466	193,588	187,564	193,588	193,588
Mean of dep. variable	2.07	15.68	18.39	33.31	10.5	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel C4: Different specification - Using a Random Effects model						
Any cyclone within 30 km	5.91***	0.71	1.6	33.10**	2.18***	1.58**
	[0.71]	[0.93]	[0.99]	[13.50]	[0.84]	[0.62]
Observations	126,326	204,466	193,588	187,564	193,588	193,588
Number of unique persons	16,613	21,815	20,805	19,119	20,805	20,805
Mean of dep. variable	2.07	15.68	18.39	33.31	10.50	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel C5: Different specification - Excluding some time variant variables such as education, marital status, household size and major city						
Any cyclone within 30 km	6.10***	0.7	1.61	31.67**	2.30***	1.65***
	[0.73]	[0.96]	[1.03]	[13.44]	[0.86]	[0.62]
Observations	126,326	204,466	193,588	187,564	193,588	193,588
Number of unique persons	16,613	21,815	20,805	19,119	20,805	20,805
Mean of dep. variable	2.07	15.68	18.39	33.31	10.50	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel C6: Different specification - Including an interaction between state/territory and year dummies						
Any cyclone within 30 km	5.74***	0.8	1.58	33.17**	2.49**	1.75**
	[0.84]	[1.09]	[1.15]	[14.06]	[0.98]	[0.72]
Observations	126,326	204,466	193,588	187,564	193,588	193,588
Number of unique persons	16,613	21,815	20,805	19,119	20,805	20,805
Mean of dep. variable	2.07	15.68	18.39	33.31	10.50	4.54
Proportion affected (%)	1.17	0.86	0.87	0.86	0.87	0.87
Panel C7: Different specification - Applying a Random Effects logit model for binary outcomes						
Any cyclone within 30 km (Marginal effects)	2.82***	0.72	1.50*		1.84***	1.39**
	[0.24]	[0.84]	[0.85]		[0.70]	[0.54]
Observations	126,317	204,466	193,588		193,588	193,588
Mean of dep. variable	2.07	15.68	18.39		10.5	4.54
Proportion affected (%)	1.17	0.86	0.87		0.87	0.87

Notes: The results presented in each column and panel are based on separate fixed-effects (FE) regressions, unless otherwise specified. Unless stated otherwise, other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level, unless indicated otherwise, in squared brackets. "Proportion affected" indicates the proportion of individuals affected by the respective cyclone exposure measure. For all binary outcome variables, denoted by [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A4: Heterogeneity in the cyclone impact on housing outcomes

	Gender		Age		Home ownership		Household income		Insurance status		Rural/urban		Coastal distance		Historical cyclone	
	Female	Male	Young	Old	Renter	Owner	Lower	Higher	Uninsured	Insured	Rural	Urban	Coastal areas	Inland areas	Cyclone-free areas	Cyclone-prone areas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Outcome:	Natural disaster related home damage															
Any cyclone within 30 km	6.38***	5.70***	5.44***	6.49***	6.02***	6.08***	5.92***	6.19***	6.77***	5.29***	8.50***	1.83**	4.92***	7.60***	5.85**	6.05***
	[1.01]	[1.04]	[0.96]	[1.13]	[1.15]	[0.95]	[1.10]	[0.97]	[1.06]	[0.99]	[1.06]	[0.72]	[0.91]	[1.19]	[2.57]	[0.78]
Observations	111,203	97,395	62,190	61,765	44,738	83,362	63,442	64,658	68,328	58,412	49,564	77,176	63,146	63,594	65,198	61,542
Number of unique persons	13,822	12,647	9,131	7,069	5,500	8,742	7,180	7,062	7,782	6,063	5,407	8,438	6,888	6,957	7,217	6,628
Mean of dep. variable	1.65	1.68	2.10	1.99	2.19	1.92	2.18	1.84	2.09	1.93	2.75	1.55	1.75	2.28	1.83	2.21
Proportion affected (%)	0.70	0.71	1.25	1.06	1.31	1.01	1.03	1.20	1.16	1.07	1.90	0.62	1.26	0.97	0.18	2.11
Outcome:	Likely to relocate															
Any category 5 cyclone within 100 km	3.16**	3.70**	3.30*	3.07**	6.24***	1.37	4.68***	1.74	4.40***	2.78	3.08**	16.94***	5.02***	2.24	3.86	3.83***
	[1.59]	[1.69]	[1.75]	[1.40]	[2.00]	[1.34]	[1.52]	[1.80]	[1.52]	[1.84]	[1.19]	[5.54]	[1.50]	[1.89]	[6.09]	[1.20]
Observations	177,805	159,616	103,313	97,446	73,781	136,913	121,246	89,448	110,019	86,161	78,435	117,745	98,504	97,676	101,418	94,762
Number of unique persons	17,766	16,741	12,539	8,941	6,992	11,116	10,026	8,082	8,705	6,372	5,954	9,123	7,580	7,497	7,875	7,202
Mean of dep. variable	14.97	15.74	23.04	7.20	22.54	12.42	15.64	16.41	17.54	13.23	16.32	15.20	16.18	15.11	14.63	16.74
Proportion affected (%)	0.35	0.36	0.63	0.54	0.70	0.48	0.57	0.55	0.62	0.53	1.36	0.06	0.70	0.46	0.06	1.14
Outcome:	Residential relocation															
Any cyclone within 30 km	1.25	2.63*	3.98***	-0.8	2.65	1.07	0.68	3.04**	3.46**	0.48	1.77	3.07*	4.29***	-0.74	6.54	1.75
	[1.38]	[1.46]	[1.52]	[1.30]	[1.75]	[1.17]	[1.42]	[1.42]	[1.42]	[1.42]	[1.25]	[1.75]	[1.35]	[1.54]	[4.06]	[1.06]
Observations	168,401	151,127	97,482	92,757	69,807	129,478	112,840	86,445	104,585	83,180	75,102	112,663	94,205	93,560	97,184	90,581
Number of unique persons	16,979	15,959	11,967	8,652	6,741	10,715	9,558	7,898	8,581	6,401	5,927	9,055	7,522	7,460	7,834	7,148
Mean of dep. variable	17.38	17.80	26.10	9.09	28.81	12.88	18.89	17.89	21.19	14.19	19.52	17.14	18.47	17.71	16.66	19.62
Proportion affected (%)	0.52	0.53	0.96	0.78	1.04	0.72	0.77	0.91	0.90	0.81	1.43	0.48	1.01	0.71	0.15	1.62

Notes: The results presented in each column and panel are based on separate fixed-effects (FE) regressions. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. "Proportion affected" indicates the proportion of individuals affected by the respective cyclone exposure measure. For all binary outcome variables, results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A4: Heterogeneity in the cyclone impact on housing outcomes (continued)

	Gender		Age		Home ownership		Household income		Insurance status		Rural/urban		Coastal distance		Historical cyclone	
	Female	Male	Young	Old	Renter	Owner	Lower	Higher	Uninsured	Insured	Rural	Urban	Coastal areas	Inland areas	Cyclone-free areas	Cyclone-prone areas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Outcome:	Relocation distance (kilometres)															
Any cyclone within 30 km	23.51	42.69**	45.65**	11.87	46.32*	22.17	33.19**	29.57	37.60**	31.47	26.43*	44.84*	55.02***	4.67	200.17**	16.77
	[17.74]	[21.26]	[20.55]	[16.15]	[24.00]	[15.87]	[16.69]	[22.03]	[17.41]	[21.66]	[15.99]	[25.98]	[19.72]	[17.99]	[85.84]	[12.60]
Observations	163,236	146,131	93,546	91,667	65,643	128,193	109,543	84,293	100,762	82,252	73,406	109,608	91,812	91,202	94,831	88,183
Number of unique persons	15,541	14,625	11,390	8,493	6,193	10,575	9,154	7,614	8,182	6,348	5,760	8,770	7,305	7,225	7,607	6,923
Mean of dep. variable	26.23	28.97	47.84	15.70	61.64	24.89	36.53	38.39	41.56	28.76	47.49	27.98	41.79	29.78	23.24	49.32
Proportion affected (%)	0.52	0.53	0.94	0.78	1.03	0.72	0.77	0.89	0.87	0.82	1.42	0.47	1.00	0.70	0.16	1.60
Outcome:	Inter-LGA relocation															
Any cyclone within 30 km	2.68**	2.01	4.33***	0.03	3.77**	1.23	1.97	2.67**	4.25***	0.17	2.48**	2.42	3.97***	0.42	4.81	2.23**
	[1.17]	[1.22]	[1.32]	[1.00]	[1.53]	[0.94]	[1.22]	[1.17]	[1.22]	[1.12]	[1.05]	[1.48]	[1.13]	[1.31]	[3.86]	[0.87]
Observations	168,401	151,127	97,482	92,757	69,807	129,478	112,840	86,445	104,585	83,180	75,102	112,663	94,205	93,560	97,184	90,581
Number of unique persons	16,979	15,959	11,967	8,652	6,741	10,715	9,558	7,898	8,581	6,401	5,927	9,055	7,522	7,460	7,834	7,148
Mean of dep. variable	10.13	10.56	14.58	4.79	16.31	7.16	10.12	10.70	11.75	7.90	10.43	9.79	10.37	9.72	9.66	10.46
Proportion affected (%)	0.52	0.53	0.96	0.78	1.04	0.72	0.77	0.91	0.90	0.81	1.43	0.48	1.01	0.71	0.15	1.62
Outcome:	Inter-state relocation															
Any cyclone within 30 km	1.74**	1.36	2.66***	0.39	2.99**	0.57	1.11	2.16**	2.77***	0.38	2.25***	0.82	3.10***	-0.14	8.12**	1.21**
	[0.84]	[0.93]	[0.98]	[0.68]	[1.17]	[0.65]	[0.81]	[0.97]	[0.91]	[0.80]	[0.79]	[1.07]	[0.87]	[0.90]	[3.52]	[0.61]
Observations	168,401	151,127	97,482	92,757	69,807	129,478	112,840	86,445	104,585	83,180	75,102	112,663	94,205	93,560	97,184	90,581
Number of unique persons	16,979	15,959	11,967	8,652	6,741	10,715	9,558	7,898	8,581	6,401	5,927	9,055	7,522	7,460	7,834	7,148
Mean of dep. variable	4.23	4.64	5.80	1.61	7.34	2.54	3.92	4.62	4.73	2.86	4.22	3.69	4.21	3.59	3.48	4.36
Proportion affected (%)	0.52	0.53	0.96	0.78	1.04	0.72	0.77	0.91	0.90	0.81	1.43	0.48	1.01	0.71	0.15	1.62

Notes: The results presented in each column and panel are based on separate fixed-effects (FE) regressions. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. “Proportion affected” indicates the proportion of individuals affected by the respective cyclone exposure measure. For all binary outcome variables, results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A5: Heterogeneity in the cyclone impact on home and content insurance purchase

	Gender		Age		Home ownership		Household income		Insurance status		Rural/urban		Coastal distance		Historical cyclone	
	Female	Male	Young	Old	Renter	Owner	Lower	Higher	Uninsured	Insured	Rural	Urban	Coastal areas	Inland areas	Cyclone-free areas	Cyclone-prone areas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Any cyclone within 30 km	3.21*	6.12***	5.48***	3.32*	2.99	5.06***	2.70*	6.26***	4.10**	4.25**	4.68***	3.82	2.98*	5.63***	2.53	4.11***
	[1.71]	[1.73]	[1.72]	[1.71]	[1.85]	[1.60]	[1.58]	[1.93]	[1.62]	[1.79]	[1.30]	[4.12]	[1.61]	[1.91]	[5.49]	[1.28]
Observations	124,567	111,377	70,763	68,963	49,260	95,559	78,966	65,853	79,462	65,357	57,036	87,783	71,930	72,889	74,257	70,562
Number of unique persons	14,767	13,725	10,050	7,428	5,758	9,323	8,233	6,848	8,707	6,374	5,957	9,124	7,454	7,627	7,878	7,203
Mean of dep. variable	48.78	49.94	47.21	54.63	28.75	61.74	39.68	63.51	31.30	73.88	47.70	52.34	51.42	49.62	52.61	48.31
Proportion affected (%)	0.42	0.42	0.74	0.64	0.73	0.64	0.67	0.67	0.71	0.63	1.60	0.07	0.82	0.52	0.07	1.30

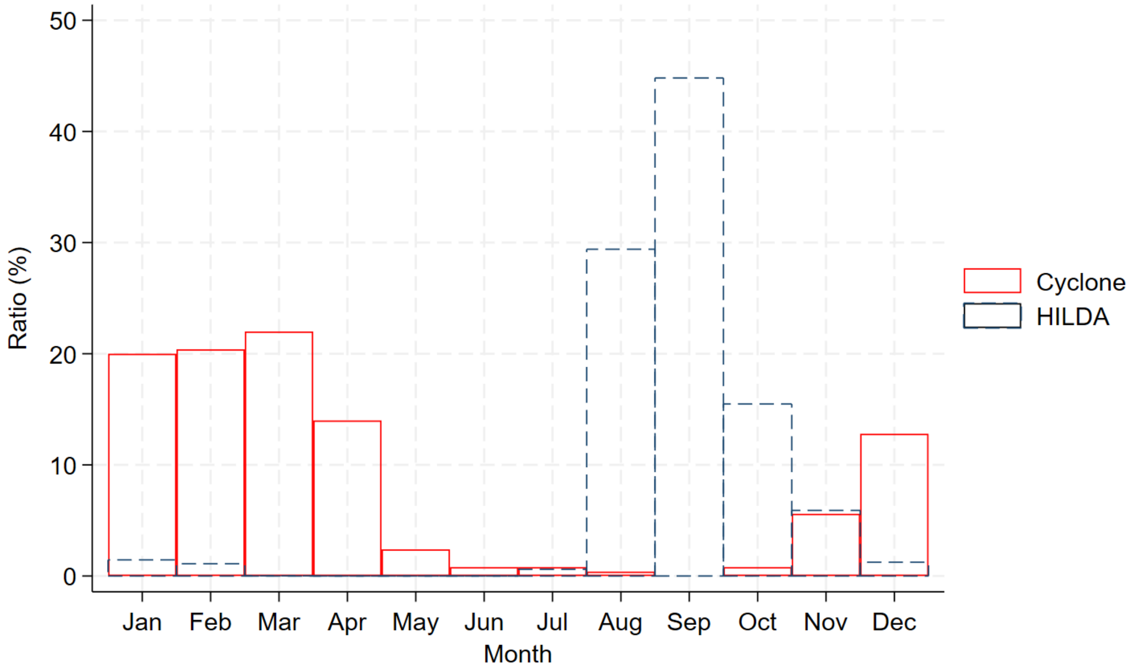
Notes: The results presented in each column and panel are based on separate fixed-effects (FE) regressions. Outcome variable: Whether the household spent $1,250 or more annually on combined home, contents, and motor vehicle insurance (adjusted to 2010 prices). Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. "Proportion affected" indicates the proportion of individuals affected by the respective cyclone exposure measure. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A6: Impact of cyclone induced home damage on migration and home insurance – An alternative instrument

Estimator:	FE	FE-IV	FE	FE-IV	FE	FE-IV	FE	FE-IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Housing outcome:	Likely to relocate [(a)]		Residential relocation [(a)]		Relocation distance (km)		Inter-LGA relocation [(a)]	
Current home damage	-0.01	1.43	4.75***	-37.69	10.92**	50.72	2.30***	-14.84
	[0.02]	[0.88]	[0.84]	[27.25]	[4.75]	[246.22]	[0.67]	[20.99]
Observations	123,939		121,934		119,307		121,934	
Number of unique persons	14,241		14,129		13,768		14,129	
Mean of dep. variable	1.91		16.92		29.96		9.39	
F statistic		85.43		88.97		85.41		88.97
Housing outcome:	Inter-state relocation [(a)]				Annual household expenditure on home, contents, motor vehicle insurance ($1,000)		Annual household expenditure on other insurance such as home, contents, motor vehicle ≥ $1,250 [(a)]	
Current home damage	0.96**	13.71			0.05*	-0.86	0.45	-3.62
	[0.40]	[13.39]			[0.03]	[1.08]	[0.84]	[30.09]
Observations	121,934				116,330		116,330	
Number of unique persons	14,129				13,845		13,845	
Mean of dep. variable	3.78				1.64		51.28	
F statistic		88.97				76.36		76.36

Notes: FE results are from the regression (2) while FE-IV results from regressions (1) and (2). "F-statistic" denotes the F statistic for the strength of the excluded instrument in the first stage regression. Instrument: Any cyclone within 100 km from its eye. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. For all binary outcome variables, indicated with [(a)], results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Robust standard errors clustered at the individual level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Figure A1: Distribution of cyclone occurrence and HILDA interview dates



Notes: Data from historical tropical cyclone observed from 2000 to November 2023 and HILDA Release 22.

Appendix B - Impact of quarterly cyclone exposure on home damage - Results by quarter

To delve into the timing of cyclone impacts, we conduct auxiliary analyses examining the influence of cyclone exposure in the one, two, three, and four quarters preceding the interview date on natural disaster-related home damage. We maintain the baseline analysis's focus on damage reported in the year before the interview but introduce four additional damage measures specific to each preceding quarter, aligning with the quarterly cyclone exposure data. The results of these analyses are presented in Appendix Table B1, suggesting substantial differences in the timing of both cyclones and natural disaster-related home damages.[28]

For example, estimates of quarterly cyclone exposure measures on the yearly home damage indicator show that the home damaging impacts are concentrated on cyclones recorded in the third and fourth quarter preceding the interview date. We also observe the same pattern, even though less pronounced in terms of the statistical significance level, in the estimates of quarterly cyclone exposure measures on the quarterly home damage indicators. This finding is consistent with the facts that tropical cyclone season in Australia is officially between November and April (BOM 2024) and most of HILDA interviews were implemented between August and October (see proportions of individuals affected by quarterly cyclones reported at the bottom of Appendix Table B1 and the timing of cyclones and HILDA surveys in Appendix Figure A1. Moreover, in line with the baseline results, the results from this experiment continue to exhibit an escalating home damage impact by cyclone category because the estimates are considerably more pronounced in terms of the magnitude and statistical significance for cyclones with a higher category.

[28] For brevity and demonstration purposes, we only report the results using 30 km within the cyclone eye. Results using other distances produce largely similar patterns. Moreover, together with the results presented in Table 2, they continue to show a diminishing home damage impact by distance from the cyclone eye.

Our analysis using quarterly measures reveals that the impact of cyclones on home damage is most evident when both events are recorded at the same time (diagonal entries in each panel of Appendix Table B1). This holds true for all cyclone exposure measures, supporting the accuracy of self-reported home damage in the HILDA survey.

Appendix Table B1: Impact of cyclone exposure on home damage - By quarter

	Natural disaster related home damage				
	Last year	Quarter 1	Quarter 2	Quarter 3	Quarter 4
Cyclone by category and time	(1)	(2)	(3)	(4)	(5)
Any cyclone within 30 km in quarter 1	-1.59	-0.48*	0.58	-0.57	0.44*
	[1.69]	[0.29]	[0.64]	[1.42]	[0.26]
Any cyclone within 30 km in quarter 2	3.91***	0.47**	2.29***	0.96**	0.06
	[0.80]	[0.23]	[0.61]	[0.40]	[0.23]
Any cyclone within 30 km in quarter 3	8.92***	-0.13	4.08***	3.25***	0.77
	[1.41]	[0.20]	[0.95]	[0.87]	[0.54]
Any cyclone within 30 km in quarter 4	8.43**	-0.08	-0.37	3.34	4.46**
	[3.28]	[0.06]	[0.33]	[2.21]	[2.21]
Observations	126,326	127,678	127,677	127,678	127,678
Number of unique persons	16,613	16,701	16,701	16,701	16,701
Mean of dep. variable x 100	2.07	0.25	0.63	0.57	0.31
Proportion affected in quarter 1 (%)	0.00	0.00	0.00	0.00	0.00
Proportion affected in quarter 2 (%)	0.64	0.64	0.64	0.64	0.64
Proportion affected in quarter 3 (%)	0.44	0.44	0.44	0.44	0.44
Proportion affected in quarter 4 (%)	0.08	0.08	0.08	0.08	0.08
Any category 5 cyclone within 30 km in quarter 1	6.15***	-0.51*	2.64***	2.64***	0.91*
	[1.20]	[0.27]	[0.91]	[0.75]	[0.51]
Any category 5 cyclone within 30 km in quarter 2	9.64***	0.15**	5.74***	2.52**	0.19
	[2.30]	[0.07]	[1.84]	[1.21]	[0.53]
Any category 5 cyclone within 30 km in quarter 3	35.30***	-0.18	16.92***	13.37***	2.64
	[4.67]	[0.18]	[3.68]	[3.35]	[1.72]
Any category 5 cyclone within 30 km in quarter 4	11.11**	-0.05	-0.51	3.71	5.95*
	[4.93]	[0.06]	[0.42]	[2.87]	[3.40]
Observations	126,326	127,678	127,677	127,678	127,678
Number of unique persons	16,613	16,701	16,701	16,701	16,701
Mean of dep. variable x 100	2.07	0.25	0.63	0.57	0.31
Proportion affected in quarter 1 (%)	0.00	0.00	0.00	0.00	0.00
Proportion affected in quarter 2 (%)	0.16	0.16	0.16	0.16	0.16
Proportion affected in quarter 3 (%)	0.09	0.08	0.08	0.08	0.08
Proportion affected in quarter 4 (%)	0.04	0.04	0.04	0.04	0.04

Notes: Results reported in each column and panel are from a separate FE regression. “Quarter 1”, “Quarter 2”, “Quarter 3”, and “Quarter 4” correspond to events that happened, respectively, within the past 0-3 months, 4-6 months, 7-9 months, and 10-12 months. Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the individual level in squared brackets. “Proportion affected” indicates the proportion of individuals affected by the respective cyclone exposure measure. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.