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Natural disasters and the demand for health insurance

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Research Summary

Why was the research done?

Natural disasters have profound repercussions on various societal aspects globally, affecting social dynamics, health outcomes, and economic stability. Scholarly inquiries have underscored the pivotal role of insurance as a primary coping mechanism adopted by individuals impacted by natural disasters to mitigate the risks associated with future calamities. However, prevailing research predominantly delves into the nexus between natural disasters and residential insurance, primarily aimed at shielding individuals from subsequent physical property damages. This exclusive focus may inadvertently overlook potential alternative strategies that affected individuals employ to mitigate future health-related risks stemming from such disasters. This study contributes to the academic discourse by broadening the scope of investigation to encompass the influence of natural disasters on the demand for health insurance.

What were the key findings?

By capitalizing on over two decades of nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey linked to historical cyclone records, this study pioneers an inquiry into the causal impacts of cyclones on the demand for private health insurance (PHI). Our findings unveil that both contemporaneous and preceding cyclones, particularly those of greater severity, substantially increase the likelihood of individuals procuring PHI. The largest estimated impact amounts to over 4 percentage points, representing approximately 8% of the sample mean and aligns with documented effects of certain PHI policies aimed at enhancing coverage. Furthermore, our findings withstand a series of sensitivity assessments, including a placebo test demonstrating that future cyclones do not impact current PHI enrolment. Moreover, the cyclone impacts are more pronounced for females, younger individuals, homeowners, affluent individuals, or those with prior residential insurance coverage, as well as residents of rural and coastal areas or historically cyclone-exposed regions. Additionally, our study furnishes suggestive evidence hinting at a potential rise in risk aversion among affected individuals as a channel through which cyclones increase PHI uptake.

What does this mean for policy and practice?

This study contributes novel and robust evidence regarding the impact of natural disasters, specifically cyclone exposure, on the demand for health insurance. The identification of an increased likelihood of PHI uptake among individuals from economically advantaged backgrounds, particularly indicated by homeownership or higher income, underscores the necessity for tailored support policies targeting vulnerable populations to utilize this natural disaster coping mechanism.

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Natural disasters and the demand for health insurance

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

Amidst growing concerns over heightened natural disaster risks, this study pioneers an inquiry into the causal impacts of cyclones on the demand for private health insurance (PHI) in Australia. We amalgamate a nationally representative longitudinal dataset with historical cyclone records, employing an individual fixed effects model to assess the impacts of various exogenously determined cyclone exposure measures. Our findings unveil that both contemporaneous and preceding cyclones, particularly those of greater severity, substantially increase the likelihood of individuals procuring PHI. The largest estimated impact amounts to over 4 percentage points, representing approximately 8% of the sample mean and aligns with documented effects of certain PHI policies aimed at enhancing coverage. Furthermore, our findings withstand a series of sensitivity assessments, including a placebo test demonstrating that future cyclones do not impact current PHI enrolment. Moreover, the cyclone impacts are more pronounced for females, younger individuals, homeowners, affluent individuals, or those with prior residential insurance coverage, as well as residents of rural and coastal areas or historically cyclone-exposed regions. Additionally, our study furnishes suggestive evidence hinting at a potential rise in risk aversion among affected individuals as a channel through which cyclones increase PHI uptake.

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1. Introduction

Natural disasters have profound repercussions on various societal aspects globally, affecting social dynamics, health outcomes, and economic stability (Dell *et al.* 2014; Carleton *et al.* 2022). Scholarly inquiries have underscored the pivotal role of insurance as a primary coping mechanism adopted by individuals impacted by natural disasters to mitigate the risks associated with future calamities (Kousky 2019; Kraehnert *et al.* 2021). However, prevailing research predominantly delves into the nexus between natural disasters and residential insurance, primarily aimed at shielding individuals from subsequent physical property damages. This exclusive focus may inadvertently overlook potential alternative strategies that affected individuals employ to mitigate future health-related risks stemming from such disasters.

This study contributes to the academic discourse by broadening the scope of investigation to encompass the influence of natural disasters on the demand for health insurance. Specifically, it pioneers an inquiry into the causal impacts of cyclones on the uptake of private health insurance (PHI) in Australia - a cyclone-prone nation endowed with a universal public health insurance system. The necessity for a fresh examination of the impact of cyclones on the acquisition of PHI is underscored by the catastrophic nature of cyclones, ranking among the most devastating extreme weather events with the potential to inflict widespread disruption and damage (Krichene *et al.* 2023; Nguyen & Mitrou 2024a). Given their profound societal implications, comprehending the ramifications of cyclones on health insurance demand is imperative for crafting efficacious policies and interventions aimed at supporting affected populations.

Furthermore, akin to other natural disasters, cyclones have been documented to engender adverse effects on income, physical health, and mental well-being (Currie & Rossin-Slater 2013; Hsiang & Jina 2014; Bakkensen & Mendelsohn 2016). These deleterious repercussions can exacerbate financial and health vulnerabilities, potentially altering individuals' risk perceptions and their inclination towards investing in health insurance coverage. Thus, an investigation into the interplay between cyclones and health insurance uptake offers invaluable insights into the broader socioeconomic repercussions of such calamities, thereby informing strategies to mitigate their adverse impact on public health and welfare.

By examining the impact of cyclones on the demand for health insurance, this study intersects with two distinct lines of research. Firstly, it contributes to the extensive literature exploring the social and economic ramifications of climate change (Dell *et al.* 2014; Carleton & Hsiang 2016).[1] Within this substantial body of work, our investigation closely aligns with studies investigating the relationship between natural disasters and insurance, which have predominantly concentrated on residential insurance, with a few exceptions (for comprehensive reviews, refer to Kousky (2019); Kraehnert *et al.* (2021)). Notably, Fier and Carson (2015) utilize state-level data from the United States (US) to identify a significant positive association between catastrophes and various indicators of life insurance demand. Additionally, recent research by Barnes *et al.* (2023) employs repeated cross-sectional individual-level data from the US and a difference-in-differences approach to demonstrate an increase in health insurance rates among individuals affected by natural disasters.

Secondly, this study intersects with a rich body of literature examining the global demand for health insurance (Besley *et al.* 1999; Cutler & Zeckhauser 2000; Propper *et al.* 2001; Nguyen & Leung 2013). Within this domain, our research aligns more closely with numerous Australian studies investigating the influence of various factors such as income, health status, and policy interventions on PHI enrolment (Cameron & Trivedi 1991; Stavrunova & Yerokhin 2014; Buchmueller *et al.* 2021; Kettlewell & Zhang 2024). However, none of these prior

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[1] Our research also relates to studies on impacts of cyclone/hurricane/typhoon on other outcomes such as migration (Mahajan & Yang 2020; Sheldon & Zhan 2022; Nguyen & Mitrou 2024b), economic growth (Hsiang & Jina 2014), income (Deryugina *et al.* 2018; Groen *et al.* 2020) and health (Currie & Rossin-Slater 2013; Bakkensen & Mendelsohn 2016).

Australian studies have delved into the relationship between natural disasters and PHI enrolment, which constitutes the primary focus of our investigation.

By capitalizing on over two decades of nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey linked to historical cyclone records, this study investigates the impact of cyclones on the demand for PHI. This inquiry contributes in several key ways to the existing literature.

Firstly, our research pioneers a comprehensive analysis of cyclone effects on PHI demand within the unique context of Australia. Unlike the US, Australia operates a universal public health insurance program, Medicare, which provides subsidized medical services and medications alongside free access to public hospitals (Duckett & Nemet 2019). By scrutinizing the repercussions of cyclones on the demand for PHI, our study sheds light on Australian responses to these calamitous events. This understanding is vital for devising effective policies to mitigate the social and economic consequences of cyclones, not only for Australia but also for other nations prone to natural disasters with similar health systems (Carleton & Hsiang 2016).

Secondly, our study benefits from the utilization of unique and high-quality datasets, enabling several methodological and empirical contributions. Leveraging a comprehensive longitudinal individual panel dataset allows us to employ an individual fixed-effects model, effectively controlling for unobservable individual time-invariant factors (Dell *et al.* 2014). This approach enables the quantification of cyclone effects on health insurance demand for the first time. In contrast, prior US studies employed state-level or repeated cross-sectional individual-level data, precluding control for individual fixed effects (Fier & Carson 2015; Barnes *et al.* 2023).[2]

[2] Barnes *et al.* (2023) acknowledge that a potential criticism of their analysis lies in the possibility that respondents affected by natural disasters and who opted to purchase health insurance may possess differing preferences compared to those who did not. In response to this critique, they employ a propensity score matching approach, which, however, is limited in its capacity to address unobservable individual factors.

Additionally, our study innovatively utilizes various exogenously recorded measures of natural disaster exposure, addressing concerns of confounding influences from human behaviours (Hsiang & Jina 2014; Guiteras *et al.* 2015).[3] These measures are applied within an individual fixed-effects model, resolving issues of unobservable individual factors correlated with both natural disaster exposure and insurance purchase behaviours.

Furthermore, the richness of our data enables an extensive heterogeneous analysis, exploring differential responses to over 50 cyclones of varying severity levels across diverse sub-populations. This analysis illuminates the channels through which cyclones influence health insurance choices and identifies vulnerable groups and regions for targeted support and resilience-building strategies (Kraehnert *et al.* 2021).

Utilizing an individual fixed effects regression model, this study elucidates four principal findings. Initially, our analysis reveals that both contemporary and antecedent year cyclones, notably those characterized by heightened severity and closer proximity, significantly escalate the acquisition of PHI. The most substantial estimated impact, amounting to 4.15 percentage points, closely mirrors the effects observed with certain policies aimed at augmenting enrolment rates within Australia. Secondly, our findings withstand rigorous scrutiny through a battery of sampling and specification tests, inclusive of direct control for various time-variant variables such as income and health. Furthermore, the robustness of our results is corroborated by outcomes from a placebo test, underscoring the absence of influence from future cyclones on current PHI enrolment.

Thirdly, our extensive heterogeneity analyses unveil nuanced variations in coping strategies contingent upon cyclone severity and diverse individual, household, and locality

[3] In particular, Fier and Carson (2015) delineate a catastrophe as any event that impacts states and leads to significant insured property loss. Conversely, Barnes *et al.* (2023) categorize a parish as a disaster-prone area once it has been officially declared as such.

characteristics. Specifically, the propensity to adopt this mitigation strategy is contingent upon the severity of cyclones, with individuals exhibiting a response predominantly to the most severe occurrences. Additionally, the analysis exposes a predilection among individuals possessing specific traits, including females, younger demographics, homeowners, individuals of higher socioeconomic status, or those with prior residential insurance coverage, as well as inhabitants of rural and coastal regions or historically cyclone-affected areas, to procure PHI in reaction to cyclonic events. Lastly, this study provides suggestive evidence hinting at a potential surge in risk aversion among affected individuals, precipitating a proactive approach towards PHI acquisition as a protective measure against future health-related uncertainties.

The remainder of this paper is structured as follows: Section 2 delineates the data and sample characteristics, while the empirical model is expounded upon in Section 3. Section 4 elucidates the principal findings, and Section 5 outlines the robustness checks conducted. The heterogeneous effects of cyclones are scrutinized in Section 6, and Section 7 delves deeper into the nexus between cyclones and health insurance behaviours. Finally, Section 8 encapsulates the conclusions drawn from the study.

2. Data and sample

2.1. Data

In this study, we draw upon two primary data sources. The first dataset originates from the Household, Income and Labour Dynamics in Australia (HILDA) survey, a nationally representative survey that commenced in 2001. This longitudinal survey encompasses 7,682 households and over 19,000 individuals, tracking individuals aged 15 years and above within private households annually. It furnishes comprehensive individual and household-level data, including residential details, health indicators, and labour market engagements (Summerfield *et al.* 2023). A notable advantage of HILDA is its ability to track individuals who relocate, allowing for observations both pre and post-cyclone events, facilitating the application of an individual fixed effects regression model to robustly ascertain the causal impact of cyclones on PHI enrolment. We utilize the latest HILDA release spanning 22 waves (2001-2022).

The second data source comprises a publicly available historical cyclone database obtained from the Australian Bureau of Meteorology (BOM). This database offers extensive information on all tropical cyclones occurring south of the equator between longitudes 90E and 160E. For each recorded cyclone, it includes details such as the track (longitude, latitude, and time) and measures of strength, including wind speed and gusts.

Integration of these datasets involves matching the cyclone's trajectory and timing from the historical database with the individual's residential postcode centroid and interview date from HILDA. We utilize the restricted version of HILDA containing postcodes, as they provide the highest geographical granularity available.

2.2. Cyclone exposure measures

Following the approach outlined by Nguyen and Mitrou (2024b), we ascertain an individual's exposure to cyclones within a given year by combining the distance to the cyclone's eye and its category. Initially, we determine the closest distance between the individual's postcode centroid and the cyclone's eye, recognizing the eye as the central region of calm surrounded by the cyclone's most potent winds, where areas directly beneath its path typically experience the severest damage (BOM 2024). This methodology, previously employed in US studies (Currie & Rossin-Slater 2013; Deryugina & Marx 2021), employs three distance bands - 30 km, 60 km, and 100 km - to evaluate exposure and damage patterns across various impact zones.

Additionally, drawing from prior research (Hsiang & Narita 2012), we gauge cyclone exposure based on its category, ranging from 1 (weakest) to 5 (strongest), employing the BOM’s prescribed cutoffs derived from maximum mean wind speed (BOM 2024). Specifically, the maximum mean wind speed (in km/h) cutoffs for cyclone categories 1 through 5 are as follows: ≤88, >88 and ≤117, >117 and ≤159, >159 and ≤199, and > 199 km/h, respectively.

To streamline the analysis and address the infrequent occurrence of yearly cyclones, we consolidate several categories into four overlapping groups: all cyclones, categories 1 to 2, categories 3 to 4, and category 5 only. Each group is then combined with the nearest cyclone path distance to the individual's residential postcode centroid, resulting in a set of 12 variables measuring cyclone exposure, each identified by cyclone category and distance to the cyclone eye. Furthermore, given the sporadic nature of yearly cyclone incidents during the study period, we incorporate a dummy variable indicating whether a cyclone was documented within the individual's residential postcode in the 12 months preceding the survey date. We specifically focus on cyclones recorded within 12 months prior to the interview date, aligning with the timing of PHI coverage in HILDA, which references "the last financial year".[4] Moreover, owing to variations in survey dates among individuals, those residing in the same postcode may experience differing exposures to the same cyclone within the same survey year.

2.3. Private health insurance measure

We construct our primary dependent variable, referred to as "private patient hospital cover" (PPHC) or "hospital cover" for brevity, based on responses to a specific question: "Were you covered by private patient hospital cover for the whole of the last financial year?" This binary variable takes the value of one if an individual answers "yes" to the question and zero if they answer "no".

While HILDA includes other measures related to PHI, we prioritize this PPHC measure for two main reasons. Firstly, it represents the predominant form of PHI in Australia and is the

[4] The financial year in Australia runs from 1st July of one calendar year to 30th June of the following calendar year. Throughout our study period spanning from 2011 to 2023, a dominant portion of HILDA interviews (92%) occurred within the concentrated period from August to October (Refer to Appendix Figure A2). Remarkably, nearly all observed cyclones (96%), spanning all categories, transpired within the timeframe of November to April during this study period.

focal point of PHI policies (Duckett & Nemet 2019). In Australia, Medicare, the universal public health insurance program, provides free access to public hospitals and subsidized medical services, while PHI offers additional benefits such as access to private hospitals and a broader choice of care providers. Among individuals in the HILDA sample with PHI coverage,[5] approximately 79% reported having "both hospital and extra cover", 12% reported "hospital cover only", 8% reported "extra cover only", and 1% reported "don't know". It's important to note that "extras" cover, including services like optical, dental, physiotherapy, and chiropractic treatment, does not constitute PPHC, which remains the focus of PHI policies (Duckett & Nemet 2019).[6] Secondly, this measure provides precise information on PHI coverage at the individual level and is consistently available on an annual basis in HILDA data from Wave 12 onwards, offering a sufficient number of observations for us to robustly assess the impact of cyclones.

2.4. Sample

Our primary unit of analysis is the individual, primarily due to the individual-level measurement of PHI coverage. In our baseline analysis, we concentrate on states and territories affected by at least one cyclone during the study duration. This selection enhances the accuracy of individual fixed effects estimates for those exposed to cyclones, as cyclone exposure remains constant over time in regions unaffected by such events (Wooldridge 2010). As a result, our baseline sample comprises New South Wales, Queensland, Western Australia, and the Northern Territory. Appendix Figure A1 illustrates the geographic distribution of cyclone

[5] The data regarding this PHI coverage measure is derived from responses to another question: "Apart from Medicare, are you currently covered by private health insurance?" This inquiry is included in Waves 4, 9, 13, 17, and 21 of the survey. Similarly, inquiries about specific types of PHI coverage are also confined to these waves. As mentioned earlier, we refrain from utilizing these PHI indicators because they are only asked every 4 years, and the number of observations is insufficient for a robust analysis. HILDA also furnishes data on annual household expenditure on PHI starting from Wave 5. However, we choose not to utilize this expenditure indicator due to several reasons. Firstly, this information is not available at the individual level. Secondly, it suffers from substantial missing data due to non-response. Finally, it is more susceptible to reporting errors, as highlighted in previous research (Nguyen *et al.* 2023).

[6] For instance, policies like the Lifetime Health Cover (LHC) and the Medicare Levy Surcharge (MLS) penalize individuals who do not hold private patient hospital cover under certain circumstances (Duckett & Nemet 2019).

impacts during the study period. Additionally, we confine the primary sample to data from Wave 12 onwards, as the principal PPHC indicator is unavailable in earlier waves.

Furthermore, we stipulate that individuals must be aged 15 years or older, as younger individuals are not surveyed in the HILDA dataset. Additionally, they must have been observed at least twice during the study period, as our primary empirical model relies on individual fixed effects. Considering these criteria, the final dataset for the primary analysis encompasses 103,280 individual-year observations derived from 15,457 distinct individuals over an 11-year period, facilitating an examination of the cyclone's impact on the principal PPHC measure.

3. Empirical model

In accordance with the methodology outlined by Nguyen and Mitrou (2024b), we employ an individual fixed effects (FE) model to examine the effects of cyclones on outcome Y for individual i, residing in postcode p, at time t:

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

Here, $Z_{i(p)t}$ is a binary variable denoting whether the individual i living in postcode p experienced a cyclone in the 12 months prior to the survey time. X_{it} represents a set of time-variant explanatory variables. δ_i accounts for individual time-invariant unobservable factors, and ε_{it} denotes the idiosyncratic error term. α, β and γ are parameters to be estimated, with β serving as our parameter of interest.

To mitigate potential confounding effects, we incorporate a limited number of individual and household-level time-variant variables into X_{it}. These variables include the individual's age (and its square), marital status, education level, household size and major city residency. We also address temporal disparities in outcomes by including dummy variables for survey month and year separately. Regional discrepancies are addressed through the inclusion of state/territory dummy variables in Equation (1). Furthermore, we consider local socio-economic contexts that may influence individual behaviours by incorporating regional unemployment rates and a relative socio-economic disadvantage index.

Given the presence of multiple observations per individual, we employ an individual FE regression, accounting for individual heterogeneity, including residential preferences, in Equation (1). This approach is essential as it allows us to control for individual unobservable time-invariant factors, particularly pertinent given findings suggesting that areas more prone to natural disasters tend to exhibit higher levels of disadvantage (Dell *et al.* 2014; Botzen *et al.* 2019). Our estimates of the cyclone impact (β) stem from yearly variations in cyclone occurrences within a postcode for the same individuals. This, combined with the stochastic nature of cyclone impacts despite spatial clustering, bolsters causal inference strength.

As discussed in Section 2.2, we define cyclone occurrences within 12 months preceding the survey date. Aligning survey dates with cyclone occurrences strengthens identification assumptions. Notably, variations in survey and cyclone dates mean individuals residing in the same postcode may experience differing cyclone exposures to the same cyclone within the same survey year (refer to Appendix Figure A2 for the distribution of survey and cyclone timing). To address potential serial correlation issues, we cluster standard errors at the individual level, as the treatment varies for the same individual over time (Cameron & Miller 2015). In robustness checks, we also present results with standard errors clustered at the postcode level or with additional postcode fixed effects, yielding largely similar findings.

4. Main results on impacts of cyclones on health insurance enrolment

4.1. Descriptive results

Table 1 presents descriptive statistics for key variables, disaggregated by cyclone exposure status. Merely 7% of individuals within our analytical sample encountered at least one cyclone within 100 km of their residence throughout the study duration, constituting our "treated" group.[7] Those impacted tend to exhibit characteristics such as youthfulness, lower educational attainment, and rural residency, contrasting with the unaffected "control" group. Noteworthy is the lower unemployment rates observed in regions housing the "treated" group; however, these areas manifest a diminished overall socioeconomic status, as indicated by the SEIFA index. Correspondingly, our data reveal a slight decrement in PPHC among affected individuals. Nevertheless, as elucidated in Section 3, these disparities may not exclusively stem from cyclone influences but rather pre-existing disparities impacting both exposure and PHI outcomes. Subsequent analysis addresses this pivotal concern.

4.2. Main regression results

Table 2 presents the cyclone estimates derived from our preferred individual FE regressions, which control for both observable time-variant and unobservable time-invariant factors. The results (Panel A) underscore significant concurrent impacts of cyclones on the likelihood of individuals having private patient hospital cover (PPHC). Notably, the positive and highly statistically significant ($p < 0.01$) estimates associated with all category 5 cyclone exposure measures suggest that individuals affected by any category 5 cyclone exhibit an increased probability of having PPHC, regardless of the distance considered. For example, individuals affected by a category 5 cyclone within 100 km from its eye are 3.19 percentage points (pp) more likely to have PPHC than unaffected counterparts.

Furthermore, the analysis reveals a positive correlation between cyclone intensity and its impact on PPHC enrolment, with estimates exhibiting greater statistical significance and

[7] Table 1 reveals that 7,175 year-observations, corresponding to 5,647 distinct individuals, are categorized as "treated," providing a sufficiently robust sample size for capturing cyclone effects effectively. Moreover, the last column in Appendix Table A1 demonstrates that despite the relatively infrequent incidence of yearly cyclones during the study period, our sample encompasses a significant number of individuals exposed to various cyclones, thereby facilitating the credible detection of potential effects. However, it is noteworthy that the number of individuals affected by more severe cyclones, particularly those in closer proximity or of higher category, is relatively small. For instance, the minimum count of individuals affected is 311, exposed to a category 5 cyclone within 30 km. Consequently, caution is warranted when interpreting results associated with such cyclone exposure measures.

magnitude for more severe cyclones. Additionally, the estimated effect of cyclones on PPHC enrolment substantially diminishes as the distance from the cyclone's eye increases. For instance, the estimated likelihood of having PPHC decreases by 30% (from 4.15 pp to 3.19 pp) when comparing individuals residing 30 km and 100 km from the eye of a category 5 cyclone. These results underscore the pivotal roles played by both cyclone intensity and geographical proximity in shaping individual responses to these natural disasters.

Acknowledging the time delay involved before observable changes in insurance behaviours post-cyclones (Kousky 2019; Kraehnert *et al.* 2021; Nguyen & Mitrou 2024b), we investigate the dynamic effects of cyclones on health insurance enrolment decisions. To address this temporal aspect, we introduce an additional variable in Equation (1) to represent exposure to cyclones one year prior to the assessment of health insurance outcomes.[8] The estimates for both concurrent and lagged cyclone exposure are delineated in Panel B of Table 2. Notably, the findings pertaining to simultaneous cyclone exposure closely align with the baseline results in Panel A, thereby reinforcing our earlier findings.

Furthermore, the estimates associated with certain lagged cyclone exposure measures demonstrate positive and statistically significant values, indicating delayed impacts of cyclones on PPHC acquisition. For example, individuals residing in a postcode within 100 km from the path of a previous category 5 cyclone exhibit a 2.96 pp increase ($p < 0.01$, Panel B - Column 12) in the likelihood of possessing PPHC in the subsequent survey wave. Moreover, consistent with the observed trends in the immediate impacts aftermath of cyclones, the estimates suggest an amplified influence of cyclones on future PPHC acquisition for more severe cyclones. Specifically, the estimates of lagged cyclone exposure demonstrate high statistical significance (i.e., $p < 0.05$) exclusively for category 5 cyclones. Additionally, the estimated impact of lagged

[8] Despite our decision to abstain from incorporating additional lags owing to constraints posed by sample size, the results exhibit considerable robustness even when adjusting for cyclone exposure occurring two years earlier (results not presented and will be available upon request).

cyclones on PPHC enrolment notably diminishes with increasing distance from the cyclone's eye. For instance, the estimated probability of possessing PPHC decreases by 25% (from 3.72 pp to 2.96 pp) when comparing individuals residing 30 km and 100 km from the eye of a category 5 cyclone.

5. Robustness checks

To enhance the robustness of our findings, we conducted a series of sampling and specification tests. For brevity, we present results based on a single cyclone exposure measure: residency in a suburb affected by any cyclone category 5 within 100 km of the eye, one year prior to the survey time. Comparable results using alternative metrics are available upon request.

Our initial sampling test involved including only individuals residing in Local Government Areas (LGAs) impacted by at least one cyclone within 100 km during the study period. This test addressed concerns regarding the adequacy of cyclone exposure variation in the baseline sample. Results from this more restricted sample are detailed in Table 3 - Panel A - Column 2. Encouragingly, these findings closely aligned with the baseline results (reiterated in Panel A - Column 1), albeit with slightly smaller magnitude (2.23 pp compared to 3.19 pp in the baseline) and less statistical significance (i.e., at the 5% level compared to the 1% level in the baseline), despite the much-reduced sample size. A similar trend was observed when analysing the entire dataset (Panel A - Column 3).

We additionally performed an experiment wherein individuals who relocated between adjacent survey waves were excluded from the original sample. This was done to isolate the potential influence of cyclones on migration, a factor previously identified in Australian research (Nguyen & Mitrou 2024b). The resulting estimate from this experiment, presented in Panel A - Column 4, closely resembled the baseline estimate. This suggests that our findings are not influenced by the potential impact of cyclones on migration.

We proceed to assess the robustness of our findings through a series of specification checks. Initially, we enhance our individual FE regression by introducing postcode dummies to address concerns regarding potential associations between cyclone exposure, outcomes, and unobservable time-invariant factors at the postcode level (results in Panel A - Column 5). Additionally, we cluster the estimates at the postcode level rather than the individual level in the baseline analysis (Panel A - Column 6). Subsequently, we employ a regression model without individual fixed effects, represented by either a pooled Ordinary Least Squares (OLS) regression estimator (Panel A - Column 7), or a Random Effects (RE) model (Panel A - Column 8).[9]

We then exclude certain time-variant variables, such as education, marital status, household size, and urban residency, from the regression (Panel A - Column 9), as they may be influenced by cyclone events. Conversely, we additionally and separately control for each of several other time-variant variables which may have been concurrently affected by cyclones (Nguyen & Mitrou 2024a). These variables include the individual's labour market income, irregular income, normalized household total disposable income, the individual's self-rated health, long term health condition, Short-Form (SF) 36 general health summary, SF36 physical health summary, and SF36 mental health summary. Estimates from these robustness checks are reported in Panel B - Columns 1 to 8, respectively. Finally, we apply a Random Effects logit model,[10] acknowledging the binary nature of the PHI coverage status (Panel B - Column 9).

Throughout these 15 specification tests, our findings demonstrate resilience to alterations in model specifications and estimation methodologies. An exception is the pooled OLS estimate,

[9] To address potential confounding effects, we included time-invariant variables, such as gender and migration status, in these specifications.
[10] A fixed effects logit model failed to converge, likely due to the relatively large sample size and the extensive use of dummy variables. As detailed earlier, we accounted for numerous time-invariant variables in this Random Effects regression. Additionally, we present the estimates in marginal effects after logit regressions to ensure comparability with those in the baseline regression.

which remains positive but is smaller in magnitude (i.e., the pooled OLS estimate is 2.63 pp compared to 3.19 pp in the baseline FE estimate) and marginally statistically significant at the 10% level. This significant decrease in magnitude and statistical significance, when observed alongside the result for a Hausman test (F-statistics unreported), confirms strong correlation within individual error terms, further supporting the use of an individual FE model.

We further validate our findings through a placebo test, wherein we incorporate lagged and leaded cyclone exposures into the equation featuring individual fixed effects (1).[11] Our premise is that, by controlling for individual fixed effects and current and lagged cyclones, future cyclones - arising randomly and unexpectedly - should not exert influence on the current demand for health insurance. The outcomes of this placebo test are delineated in Panel A of Table 4, revealing two primary observations. Firstly, the estimates of current and lagged cyclones closely mirror the baseline results (as depicted in Panel B of Table 2), thus reinforcing the robustness of our findings. Secondly, all estimates pertaining to leaded cyclones lack statistical significance, affirming the exogeneity of cyclones and our ability to capture their causal impact on health insurance demand.

Panel B of Table 4 reproduces the findings elucidated by Nguyen and Mitrou (2024b), indicating that exposure to any category 5 cyclone similarly prompts individuals to procure home or contents insurance.[12] For example, the results indicate that individuals affected by any

[11] For the sake of brevity and focus, this and subsequent subsections concentrate on category 5 cyclones due to their demonstrated significant effects in our previous findings. Outcomes for alternative cyclone measures can be provided upon request.

[12] Following the methodology outlined by Nguyen and Mitrou (2024b), individuals are categorized as "likely had residential insurance cover" if their household's annual expenditure on combined home, contents, and motor vehicle insurance amounts to $1,250 (adjusted to 2010 prices) or more. Conversely, individuals whose household expenditure falls below this threshold are classified as "uninsured". Data concerning home and contents insurance are obtained from responses to a question regarding annual household spending on "other insurance (home/contents/motor vehicle)", available from Wave 6 onwards. As elucidated in Nguyen and Mitrou (2024b), the $1,250 cutoff is determined based on its equivalence to the average annual premium for comprehensive car insurance for a family household with a young driver during the corresponding period. This selection criterion is supported by the observed trend wherein nearly all (90%) households in the dataset possess comprehensive vehicle insurance coverage, thereby indicating that households surpassing the $1,250 threshold are likely to be equipped with residential insurance.

category 5 cyclone within a 100 km radius from its eye in the preceding 12 months are approximately 4.89 pp more inclined to obtain residential insurance coverage in the same year. This observation substantiates existing research on the implications of natural disasters on property insurance uptake, positing that insurance serves as a coping mechanism to alleviate the financial repercussions incurred by such events (Kousky 2019; Kraehnert *et al.* 2021).

Moreover, while not directly comparable, contrasting the magnitude of the estimated impacts of the same cyclone exposure measures on two insurance types reveals a significantly greater effect on residential insurance than on PPHC uptake. For instance, the estimates of current cyclones show that exposure to any category 5 cyclone within 100 km of its eye increases the likelihood of having residential insurance approximately 1.72 times (≈4.89/2.84) greater than its impact on the probability of purchasing PPHC. This heightened cyclone impact on residential insurance suggests that affected individuals may prioritize this type of insurance to help them mitigate the future home damage caused by cyclones. This inference aligns with the findings presented by Nguyen and Mitrou (2024a), where cyclones substantially cause home damage but do not directly affect health.

In summary, the results from this section demonstrate the robustness of our findings across various sampling and methodological tests, including a placebo examination, implying that our estimates likely accurately reflect the genuine causal effects of cyclones on health insurance acquisition.

6. Heterogeneous cyclone impacts on health insurance enrolment

To illuminate the potential mechanisms through which cyclones influence health insurance acquisition and to identify conceivable barriers to this coping strategy (Kousky 2019; Kraehnert *et al.* 2021), we investigate likely heterogeneity across various sub-populations. Drawing from the approach outlined by Nguyen and Mitrou (2024b), we employ an individual FE model (1) to estimate effects within distinct groups defined by nine individual, household, or regional characteristics. Specifically, individual characteristics include gender (male vs. female), age group (young vs. old, categorized relative to the median population age), and health status ("poor health" vs. "good health").[13]

Additionally, household attributes encompass homeownership status (renters vs. homeowners), income group (lower income vs. higher income households, defined relative to the median of the real normalized household income), residential insurance status (insured vs. uninsured), 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 of approximately 10 km). To mitigate concerns regarding the influence of cyclones and subsequent effects on individual or household behaviours (e.g., migration or insurance acquisition) on sub-population classification, individuals are categorized based on the values of time-variant variables (excluding age) observed at their first appearance in the sample.

Finally, the primary regional characteristic is determined by whether the individual's residing postcode experienced any cyclone within a 100 km radius of its eye within the past 30 years ("cyclone-free areas" vs. "cyclone-prone areas"). For conciseness and illustrative clarity, this section utilizes a singular cyclone exposure indicator to determine whether individuals were exposed to a category 3 to 5 cyclone within a 100 km radius of its eye. We consolidate all categories from 3 to 5 cyclones in this specific cyclone exposure metric due to their combined statistically significant impacts on PPHC in the pooled regression (Table 2 - Panel A - Columns 11 and 12) and to ensure an adequate sample size of individuals exposed to this cyclone measure across various sub-populations for a robust heterogeneous analysis.

[13] Individuals are categorized as being in "good health" if they responded with "very good" or "excellent" to the query, "In general, would you say your health is", while those who responded "poor", "fair", or "good" are classified as being in "poor health". This classification is selected to ensure a roughly equal and adequate sample size for each sub-population for a robust heterogeneous analysis.

The results of this analysis are graphically represented in Figure 1. The dashed horizontal line in Figure 1 illustrates the estimate for the entire population, which is positive and statistically significant at the 1% level. This indicates that individuals exposed to any category 3 to 5 cyclone within a 100 km radius of its eye are 1.41 pp more likely to acquire PPHC. Notably, this population estimate falls between the impacts of any category 3-4 cyclone and any category 5 cyclone combined, as reported in Table 2 - Panel A - Columns 11 and 12.

Figure 1 provides a visual representation of the regression estimates depicting cyclone impacts and the numerical sample means of the dependent variable across various subgroups within the population. It offers insights into the influence of different factors on the variation in health insurance acquisition in response to cyclones. For example, females demonstrate a heightened propensity to purchase PPHC when affected by any category 3 to 5 cyclone within a 100 km radius of its eye, as evidenced by their larger and statistically significant cyclone estimate. Intriguingly, although not directly comparable, our observation of a more pronounced impact for females aligns with findings from a recent study conducted in the US by Barnes *et al.* (2023). Similarly, younger individuals are notably more inclined to acquire this type of PHI when exposed to any category 3 to 5 cyclone within a 100 km radius of its eye, as indicated by the greater and statistically significant cyclone estimate ($p < 0.01$) specific to this subgroup. This inclination persists despite their lower baseline PPHC rate, as depicted by the reported mean figures.

Subgroup estimates based on prior health status reveal a pattern consistent with previous Australian research indicating a positive association between health and PHI coverage (Nguyen *et al.* 2023; Nguyen *et al.* 2024). In our dataset, individuals with better health are more likely to possess PPHC at baseline, comprising 57% compared to 45% of their counterparts. Additionally, cyclone estimates for this group are slightly higher, standing at 1.45 pp compared to 1.01 pp. However, the disparity in sub-group estimates is not notably discernible, as both estimates are statistically significant at the 5% level.

Furthermore, subgroup estimates based on homeownership status reveal significant disparities between homeowners and renters. Homeowners demonstrate more than double the likelihood of possessing PPHC at baseline, with a mean of 62% compared to 32% for renters. Additionally, the estimate for homeowners is over double in magnitude and statistically significant ($p < 0.01$) specifically for this subgroup. Similarly, only individuals from wealthier households, who are approximately 50% more likely to have PPHC at baseline, are statistically significantly ($p < 0.01$) more likely to purchase this type of PHI when impacted by any category 3 to 5 cyclone within a 100 km radius of its eye.

Similarly, subgroup estimations predicated on antecedent residential insurance status reveal notable disparities. Individuals residing in households likely covered by home or contents insurance are nearly twice as inclined to possess PPHC at baseline, exhibiting a mean of 67% in contrast to 34% for their counterparts. Furthermore, the cyclone exposure estimate for this subgroup surpasses twofold in magnitude and is statistically significant ($p < 0.01$) uniquely for this subgroup.

Moreover, health insurance acquisition appears to be notably prevalent among residents in rural or coastal areas, supported by statistically significant estimates ($p < 0.01$) observed solely within this demographic. Furthermore, individuals residing in historically cyclone-prone regions, who demonstrate a higher likelihood of possessing PPHC at baseline - constituting 47% compared to 54% of those in historically cyclone-free areas - are statistically significantly ($p < 0.01$) more inclined to procure this form of insurance when faced with a new cyclone event. This observation corresponds with findings from an Australian study by Nguyen and Mitrou (2024b) employing similar data and methodology, highlighting that individuals in cyclone-prone regions exhibit an increased propensity to acquire residential insurance following new cyclone occurrences. These patterns are consistent with the notion that individuals may base insurance purchase decisions on the anticipated likelihood of future natural disasters, informed by historical disaster occurrences (Kousky 2019; Kraehnert *et al.* 2021).

Overall, the aforementioned heterogeneous analysis underscores that individuals with specific characteristics - such as females, younger individuals, homeowners, wealthier individuals, or those with prior residential insurance coverage, as well as residents of rural areas, coastal areas, or historically cyclone-exposed regions - are more inclined to acquire PHI when affected by cyclones. The discovery that solely individuals from more economically advantaged backgrounds, as indicated by homeownership or higher income, exhibit a greater likelihood of obtaining private health insurance, is consistent with the findings of Nguyen and Mitrou (2024b), who observe that only those from more economically advantaged backgrounds can utilize migration and residential insurance acquisition strategies to mitigate the detrimental impact of cyclones. Collectively, these findings underscore the necessity for targeted support policies aimed at assisting vulnerable populations. However, our findings diverge from those reported in a study by Barnes *et al.* (2023) in the US, which suggest that individuals most vulnerable to disruptions - such as black, unmarried, and less educated population groups - are more likely to acquire health insurance in response to natural disasters.

7. Discussion

The findings from Section 4 underscore the significant impact of both current and lagged cyclones, particularly those of greater severity, on the likelihood of individuals acquiring PPHC. Notably, exposure to a category 5 cyclone within a 30 km radius of its eye is associated with the most substantial estimated impact, amounting to 4.15 percentage points. This impact, representing approximately 8.23% of the mean prevalence of PPHC ownership (50%) in our sample, underscores the significance of cyclone events in influencing health insurance uptake.

Furthermore, this identified impact aligns with documented effects of certain PHI policies targeting specific demographics within Australia. For instance, research by Stavrunova and Yerokhin (2014) highlights the impact of the Medicare Levy Surcharge (MLS) policy, which imposes a tax penalty on high-income earners without PPHC coverage, resulting in a 2.4 percentage point increase in private insurance coverage among single individuals. Similarly, findings from Kettlewell and Zhang (2024) demonstrate the impact of the Lifetime Health Cover (LHC) policy, which imposes penalties on those acquiring PPHC after turning 30, leading to a 1 to 4 percentage point increase in uptake.

This section evaluates the role of certain plausible factors contributing to the observed cyclone effects. Both theoretical frameworks and empirical evidence highlight a range of factors that influence the demand for health insurance (Cameron & Trivedi 1991; Cutler & Zeckhauser 2000; Barnes *et al.* 2023). These factors encompass income, health risks, premiums, and risk preferences. A prior Australian study by Nguyen and Mitrou (2024a), employing a comparable dataset and empirical approach, indicates that cyclone exposure does not significantly affect income and health, thus implying a limited role for income and health in elucidating our findings. Indeed, as demonstrated in Section 5, our results remain robust even with the direct inclusion of various income indicators, including non-labour income,[14] which encompasses any financial assistance from governmental or non-governmental sources, as well as health indicators. Taken together, these observations suggest that cyclones are unlikely to influence the demand for health insurance through the income or health channel.

[14] Although direct comparisons are hindered by disparities in research context and methodological approaches, Barnes *et al.* (2023) identify a considerable influence of natural disasters on health insurance uptake in their US study, particularly through an increase in employer-sponsored insurance. They interpret this phenomenon as evidence endorsing the notion that a substantial portion of the impact arises from post-disaster economic recovery. In contrast, as previously discussed, income - including government assistance - is unlikely to account for the observed findings in our study.

Likewise, health insurance premiums may not act as a conduit through which cyclones influence the uptake of PHI, primarily for three reasons. First, although PHI providers in Australia possess the capacity to differentiate premiums based on regional factors, such regions are typically delineated at a broad geographical scale, such as state/territory or rural/urban areas, and tend to remain consistent over time (Duckett & Nemet 2019). Consequently, it is improbable that cyclones would exert a disproportionate impact on insurance premiums for regions affected by cyclones, especially considering that these regions are defined at a much smaller geographical level (i.e., postcode level) and fluctuate over time in our empirical framework. Second, our empirical model addresses the potential fluctuations in premiums by regions over time by controlling for both region fixed effects (at the state/territory level in the baseline and at the postcode level in sensitivity tests) and time fixed effects (i.e., month and year dummies). Third, even in the hypothetical scenario where PHI premiums were to increase disproportionately for cyclone-affected regions,[15] such an increase would corroborate our finding of a positive link between cyclone exposure and PHI uptake. This is because the surge in premiums is likely to dampen the demand for PHI among individuals impacted by cyclones.

The preceding analyses have eliminated income, health status, and premiums as potential channels through which cyclones may increase PHI uptake, thus implicating risk preferences as a plausible explanation. Should this hypothesis hold, our observation of a positive association between cyclones and PHI acquisition implies that individuals affected by cyclones, particularly those impacted by severe events, may exhibit heightened risk aversion and consequently opt to purchase more PHI as a safeguard against potential future losses, notwithstanding the associated premiums. This empirical finding lends support to the economic

[15] The empirical evidence from prior research demonstrates that natural disasters can escalate residential insurance premiums (Born & Viscusi 2006; Kousky 2019; Kraehnert *et al.* 2021). This evidence base implies a potential parallel increase in PHI premiums. Such an increase can be ascribed to elevated healthcare expenses, strain on healthcare infrastructure, and the broader economic repercussions stemming from these calamities.

theory of risk preferences and its implications for health insurance demand (Kimball 1993; Cutler & Zeckhauser 2000). Moreover, it aligns with existing empirical evidence indicating that individuals tend to display reduced risk-taking behaviour, as revealed by increased health insurance enrolment, following traumatic events such as environmental pollution (Chang *et al.* 2018), military-related trauma (Shai 2022), or natural disasters (Barnes *et al.* 2023).[16]

Our recognition of the positive impact of cyclones on PHI enrolment, when juxtaposed with the existing literature highlighting the advantages of PHI in Australia (for a recent review, see Nguyen *et al.* (2024)) and international evidence on the detrimental effects of natural disasters on health (Currie & Rossin-Slater 2013; Bakkensen & Mendelsohn 2016; Carleton *et al.* 2022), suggests that acquiring PHI serves as a potential coping mechanism for individuals to shield themselves against future health-related expenses. Analogous to how residential insurance helps alleviate future residential damage caused by subsequent cyclones, as demonstrated in Nguyen and Mitrou (2024b), the acquisition of PHI may assist individuals in addressing forthcoming healthcare needs.

8. Conclusion

This study leverages a distinctive natural experiment, wherein individuals are subject to randomly timed exposure to local cyclones, enabling the inaugural causal analysis of their repercussions on the uptake of PHI in Australia. Our findings indicate a notable increase in PHI acquisition following both current and preceding year cyclones, particularly those of heightened severity and closer proximity to the individual's homes. For instance, the most substantial estimated impact, reaching 4.15 percentage points, is observed with concurrent exposure to a category 5 cyclone within a 30 km radius of its eye. This newly identified effect

[16] Although not directly comparable, our findings are consistent with experimental evidence indicating that individuals in Indonesia who have recently endured natural disasters tend to exhibit greater risk aversion (Cameron & Shah 2015). However, they diverge from the findings of Hanaoka *et al.* (2018), who observed an increase in people's willingness to take risks following the 2011 Great East Japan Earthquake.

of cyclones on PHI uptake mirrors the influence of certain policies designed to bolster enrolment rates in Australia. Furthermore, our findings withstand a series of sensitivity assessments, including a placebo test demonstrating that future cyclones do not impact current PHI enrolment.

Through extensive heterogeneous analysis, we discern that various demographic and socio-economic factors contribute to the propensity of individuals to acquire PHI in the aftermath of cyclones. Notably, females, younger individuals, homeowners, affluent individuals, or those with prior residential insurance coverage, as well as residents of rural and coastal areas or historically cyclone-exposed regions, display a heightened inclination toward PHI acquisition following cyclonic events. The identification of an increased likelihood of PHI uptake among individuals from economically advantaged backgrounds, particularly indicated by homeownership or higher income, underscores the necessity for tailored support policies targeting vulnerable populations to utilize this natural disaster coping mechanism. Additionally, our study provides suggestive evidence indicating a potential increase in risk aversion among affected individuals, leading to a proactive mitigating approach in purchasing PHI as a safeguard against future health-related expenditures.

This study contributes novel and robust evidence regarding the impact of natural disasters, specifically cyclone exposure, on the demand for health insurance. However, it is imperative to acknowledge certain limitations that delineate avenues for future research. Firstly, while our investigation provides suggestive evidence concerning the potential influence of changes in risk preferences subsequent to cyclone exposure on health insurance enrolment, the lack of comprehensive measures of risk preferences precludes definitive conclusions. Further inquiry employing datasets incorporating such measures is warranted to ascertain whether shifts in risk preferences function as a mechanism through which cyclone exposure affects health insurance enrolment. Secondly, exploring the subsequent implications of cyclone-induced health insurance acquisition on healthcare utilization and health outcomes would furnish a comprehensive understanding of the social and economic repercussions of cyclones.

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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)	44.814	45.860	-1.046***
Married/De facto [(a)]	0.629	0.633	-0.003
Separated/divorced/widowed [(a)]	0.137	0.137	0.000
Year 12 [(a)]	0.156	0.152	0.004
Vocational or training qualification [(a)]	0.407	0.383	0.024***
Bachelor or higher [(a)]	0.176	0.207	-0.031***
Household size	2.843	2.870	-0.027
Major city [(a)]	0.411	0.615	-0.204***
Local area unemployment rate (%)	5.037	5.276	-0.239***
Local area SEIFA index	5.050	5.438	-0.388***
Have PPHC [(a)]	0.492	0.505	-0.013**
Observations	7,175	96,105	

Notes: Figures are sample means. [(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 impacts of cyclone exposures on the demand for private patient hospital cover

Distance to cyclone eye:	Within 30 km				Within 60 km				Within 100 km			
Cyclone category:	Any	Cat 1-2	Cat 3-4	Cat 5	Any	Cat 1-2	Cat 3-4	Cat 5	Any	Cat 1-2	Cat 3-4	Cat 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A:	Current cyclone (Observations: 103,280; Persons: 15,457; Mean: 50.44)											
Current cyclone	0.40	-1.38	-0.38	4.15***	0.38	-0.21	0.00	2.91***	0.59*	-0.56	0.91**	3.19***
	[0.72]	[1.46]	[0.84]	[1.58]	[0.43]	[0.85]	[0.51]	[1.10]	[0.34]	[0.54]	[0.43]	[0.91]
% affected by current cyclone	1.30	0.43	0.56	0.30	3.90	1.25	2.12	0.54	6.95	2.96	3.20	0.87
Panel B:	Current and lagged cyclone (Observations: 96,928; Persons: 14,027; Mean: 51.19)											
Current cyclone	-0.38	-2.03	-0.70	2.92*	0.21	-0.57	0.03	2.70**	0.40	-0.79	0.91**	2.84***
	[0.74]	[1.55]	[0.88]	[1.68]	[0.45]	[0.89]	[0.54]	[1.20]	[0.36]	[0.58]	[0.46]	[0.98]
Lagged cyclone	1.41*	2.12	-0.34	3.72**	0.48	0.04	0.07	2.73**	0.53	0.47	-0.09	2.96***
	[0.82]	[1.89]	[0.99]	[1.57]	[0.46]	[0.98]	[0.54]	[1.10]	[0.37]	[0.63]	[0.45]	[0.92]
% affected by current cyclone	1.28	0.42	0.56	0.30	3.87	1.23	2.13	0.53	6.85	2.88	3.21	0.85
% affected by lagged cyclone	1.16	0.31	0.55	0.31	3.59	0.97	2.08	0.55	6.38	2.44	3.15	0.87

Notes: Results reported in each column and panel are from a separate FE regression. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. "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. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:	Baseline	Sample: Only LGAs with at least one cyclone within 100 km	Sample: Whole Australia	Sample: Excluding movers	Including postcode dummies	Clustering at the postcode level	Employing a pooled OLS regression model	Using Random Effects model	Excluding some time variant variables
Any category 5 cyclone	3.19***	2.23**	2.72***	3.21***	3.04***	3.12***	2.63*	3.24***	2.96***
within 100 km	[0.91]	[0.92]	[0.92]	[0.95]	[0.90]	[0.81]	[1.45]	[0.90]	[0.90]
Observations	103,280	37,613	171,233	77,499	103,235	103,235	103,280	103,280	103,280
No of unique persons	15,457	6,056	24,795	13,677	15,457	15,457		15,457	15,457
Mean of dep. variable	50.44	45.11	50.76	53.58	50.45	50.45	50.44	50.44	50.44
Proportion affected (%)	0.87	2.40	0.53	0.79	0.87	0.87	0.87	0.87	0.87
Panel B:	Including labour market income	Including irregular income	Including normalized household total disposable income	Including self-rated health	Including any long-term health condition	Including SF36 general health summary	Including SF36 physical health summary	Including SF36 mental health summary	Applying a Random Effects logit model
Any category 5 cyclone	3.16***	3.21***	3.19***	2.91***	3.24***	3.01***	3.02***	3.01***	3.50***
within 100 km	[0.91]	[0.91]	[0.91]	[0.92]	[0.91]	[0.93]	[0.92]	[0.93]	[0.91]
Observations	103,280	103,137	103,280	93,218	103,088	93,114	93,053	93,607	103,280
No of unique persons	15,457	15,451	15,457	14,762	15,437	14,736	14,744	14,751	
Mean of dep. variable	50.44	50.43	50.44	51.46	50.45	51.54	51.49	51.48	50.44
Proportion affected (%)	0.87	0.87	0.87	0.83	0.87	0.82	0.83	0.82	0.87

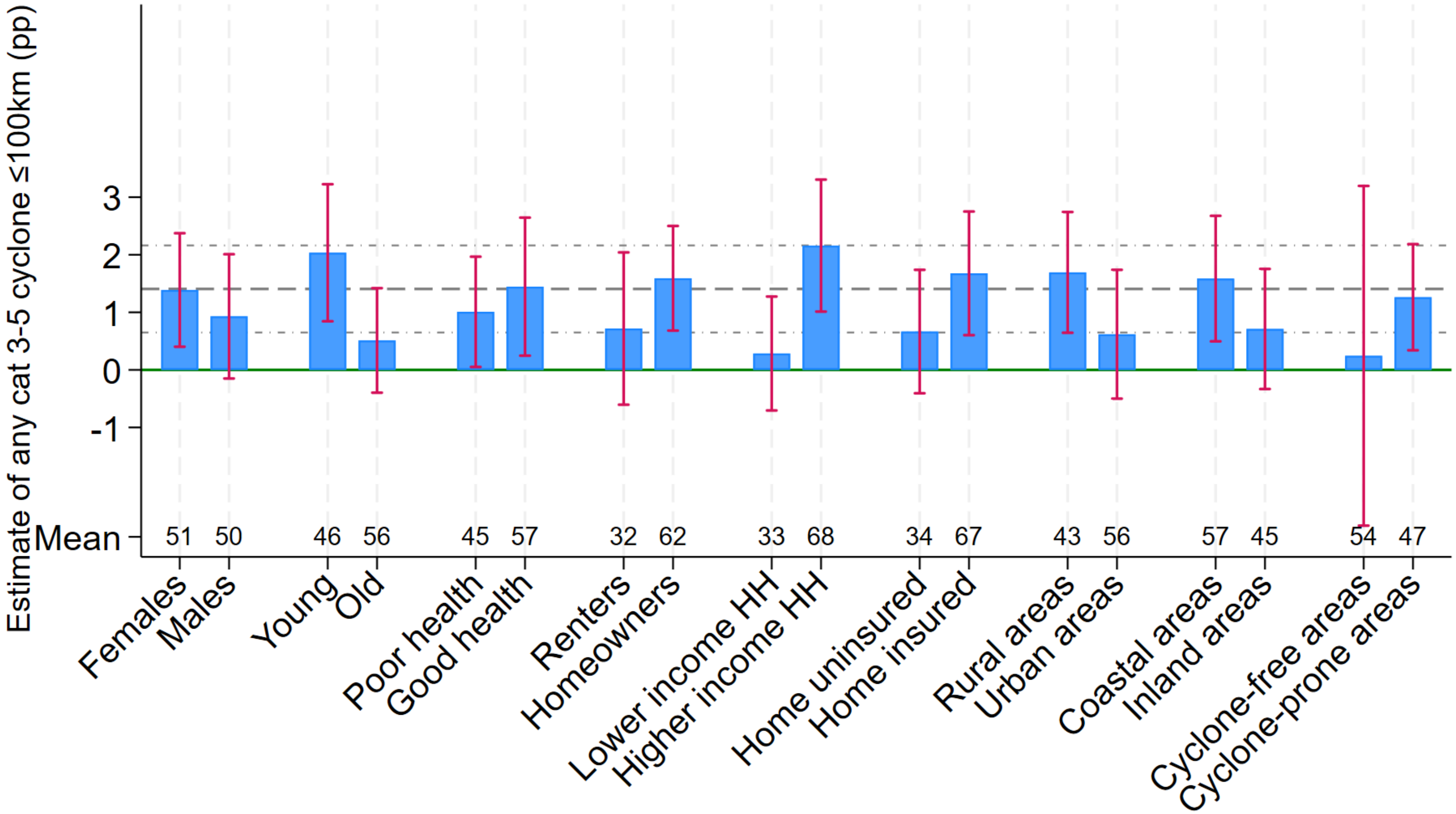
Notes: The results presented in each column and panel are based on a separate FE regression, unless otherwise specified. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Unless stated otherwise, other explanatory variables include age (and 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. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Placebo test and cycline impacts on the demand for residential insurance coverage

	Any category 5 cyclone within 30 km	Any category 5 cyclone within 60 km	Any category 5 cyclone within 100 km
	(1)	(2)	(3)
Panel A: Placebo test	Dependent variable: Private patient hospital cover (Observations: 82,640; Persons: 12,649; Mean: 51.74)		
Current cyclone	3.74**	3.04**	3.17***
	[1.88]	[1.36]	[1.10]
Lagged cyclone	4.50***	3.18***	3.22***
	[1.74]	[1.22]	[0.98]
Leaded cyclone	0.27	0.44	1.11
	[2.05]	[1.48]	[1.13]
Proportion affected by current cyclone (%)	0.33	0.60	0.96
Proportion affected by lagged cyclone (%)	0.33	0.60	0.96
Proportion affected by leaded cyclone (%)	0.32	0.57	0.93
Panel B: Additional outcomes	Dependent variable: Likely had residential insurance cover (Observations: 131,634; Persons: 15,712; Mean: 51.36)		
Current cyclone	5.06**	4.41***	4.89***
	[2.08]	[1.62]	[1.29]
Lagged cyclone	1.46	1.06	2.68**
	[1.90]	[1.51]	[1.25]
Proportion affected by current cyclone (%)	0.29	0.47	0.69
Proportion affected by lagged cyclone (%)	0.31	0.49	0.72

Notes: Results reported in each column are from a separate FE equation (1), with a one-year lagged and one-year leaded cyclone exposure measures as two additional control variables. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. “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. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 1: Heterogeneity in the cyclone impact on private patient hospital cover uptake



Notes: Results for different sub-populations are obtained from a separate FE regression. Dependent variable: private patient hospital cover. Results (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 A2.

Online Appendix

for refereeing purposes and to be published online

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)	45.79	15.00	101.00	19.16	19.86	2.58
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	0.46	0.20
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	0.34	0.31	0.13
Year 12	Dummy: = 1 if the individual completes Year 12 and zero otherwise	0.15	0.00	1.00	0.36	0.34	0.14
Vocational or training qualification	Dummy: = 1 if the individual has a vocational or training qualification and zero otherwise	0.38	0.00	1.00	0.49	0.47	0.12
Bachelor or higher	Dummy: = 1 if the individual has a bachelor degree or higher and zero otherwise	0.21	0.00	1.00	0.40	0.38	0.10
Household size	Number of household members	2.87	1.00	17.00	1.49	1.42	0.69
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	0.15
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	5.26	2.30	8.00	1.14	0.69	1.03
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area	5.41	1.00	10.00	2.86	2.69	1.05
Private patient hospital cover	Dummy variable: = 1 if responses "Yes" to the question "Were you covered by private patient hospital cover for the whole of the last financial year?", and zero otherwise	0.50	0.00	1.00	0.50	0.46	0.20

Notes: Sample of 103,280 observations.

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

Variable	Description	Mean	Min	Max	Standard deviations			Count of individuals affected
					Overall	Between	Within	
Any cyclone within 30 km	Dummy variable: = 1 if an individual's residential postcode was within 30 km of any cyclone eye last year and zero otherwise	0.013	0.00	1.00	0.11	0.06	0.10	1,338
Any cat 1 or 2 cyclone within 30 km	Dummy variable: = 1 if an individual's residential postcode was within 30 km of any category 1 or 2 cyclone's eye last year and zero otherwise	0.004	0.00	1.00	0.07	0.05	0.06	447
Any cat 3 or 4 cyclone within 30 km	Dummy variable: = 1 if an individual's residential postcode was within 30 km of any category 3 or 4 cyclone's eye last year and zero otherwise	0.006	0.00	1.00	0.07	0.03	0.07	580
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	0.003	0.00	1.00	0.05	0.02	0.05	311
Any cyclone within 60 km	Dummy variable: = 1 if an individual's residential postcode was within 60 km of any cyclone eye last year and zero otherwise	0.039	0.00	1.00	0.19	0.11	0.17	4,029
Any cat 1 or 2 cyclone within 60 km	Dummy variable: = 1 if an individual's residential postcode was within 60 km of any category 1 or 2 cyclone's eye last year and zero otherwise	0.013	0.00	1.00	0.11	0.08	0.10	1,293
Any cat 3 or 4 cyclone within 60 km	Dummy variable: = 1 if an individual's residential postcode was within 60 km of any category 3 or 4 cyclone's eye last year and zero otherwise	0.021	0.00	1.00	0.14	0.06	0.14	2,186
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	0.005	0.00	1.00	0.07	0.04	0.07	561
Any cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any cyclone eye last year and zero otherwise	0.069	0.00	1.00	0.25	0.15	0.23	7,175
Any cat 1 or 2 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 1 or 2 cyclone's eye last year and zero otherwise	0.030	0.00	1.00	0.17	0.12	0.15	3,054
Any cat 3 or 4 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 3 or 4 cyclone's eye last year and zero otherwise	0.032	0.00	1.00	0.18	0.08	0.17	3,310
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	0.009	0.00	1.00	0.09	0.05	0.09	903

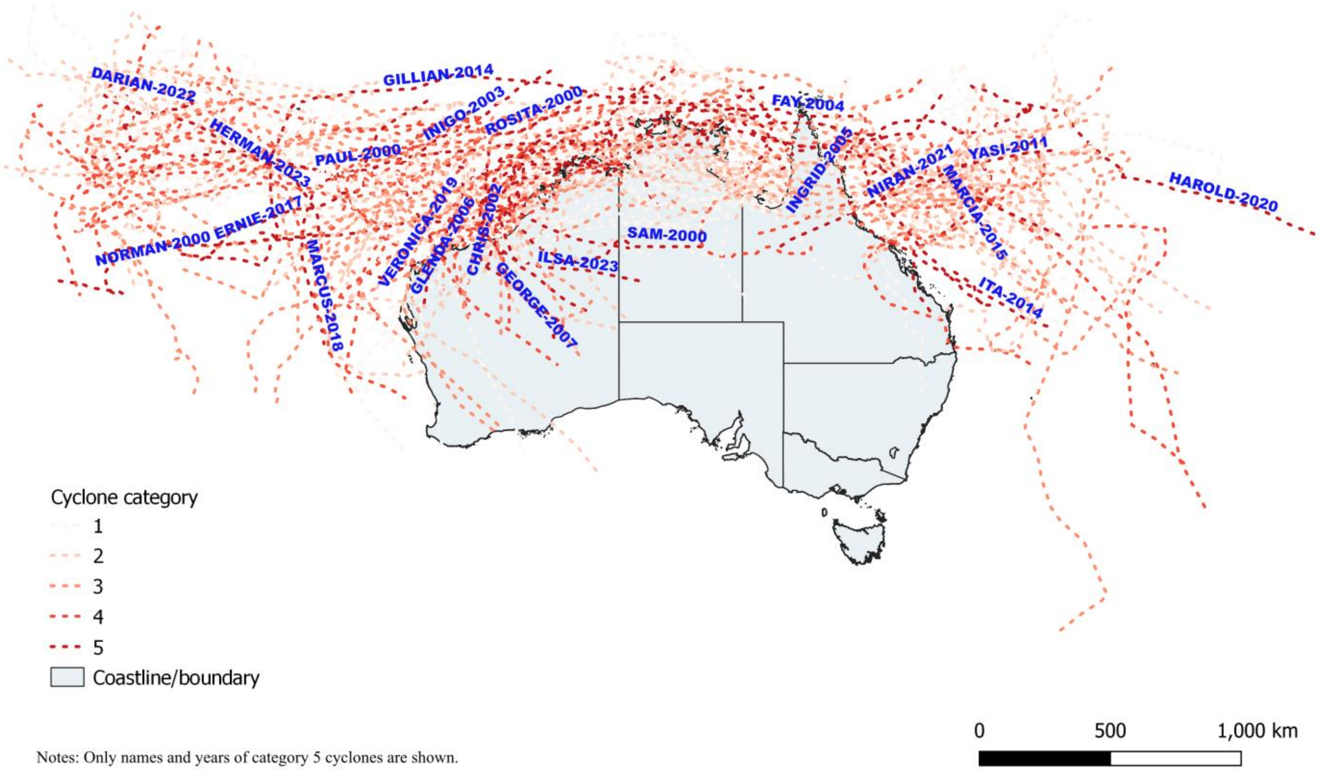
Notes: Sample of 103,280 observations.

Appendix Table A2: Heterogeneity in the cyclone impact on private patient hospital cover uptake

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Separate by	Gender		Age		Health status		Home ownership		Household income	
	Female	Male	Young	Old	Poor health	Good health	Renter	Owner	Lower	Higher
Any category 3 to 5 cyclone within 100 km	1.39***	0.93*	2.03***	0.51	1.01**	1.45**	0.72	1.59***	0.28	2.16***
	[0.50]	[0.55]	[0.61]	[0.46]	[0.49]	[0.61]	[0.67]	[0.46]	[0.50]	[0.58]
Observations	90,353	80,880	51,727	49,608	51,355	49,714	36,712	64,357	50,371	50,698
No of unique persons	12,909	11,886	8,262	6,687	6,453	6,327	4,887	7,893	6,363	6,417
Mean of dep. variable	51.09	50.40	45.50	56.11	44.65	57.45	32.09	61.70	33.45	68.33
Proportion affected (%)	2.43	2.44	4.26	3.86	4.17	3.76	4.35	3.75	4.00	3.94
Panel B: Separate by	Home insurance status		Rural/urban		Coastal distance		Community cyclone history			
	Uninsured	Insured	Rural	Urban	Coastal areas	Inland areas	Cyclone-free areas	Cyclone-prone areas		
Any category 3 to 5 cyclone within 100 km	0.67	1.68***	1.69***	0.62	1.59***	0.71	0.25	1.26***		
	[0.55]	[0.55]	[0.53]	[0.57]	[0.56]	[0.53]	[1.51]	[0.47]		
Observations	49,167	51,038	38,886	61,319	50,395	49,810	56,441	43,764		
No of unique persons	6,446	6,215	4,908	7,753	6,358	6,303	7,095	5,566		
Mean of dep. variable	34.48	67.07	43.21	56.07	56.85	45.25	54.38	46.82		
Proportion affected (%)	4.17	3.79	5.32	3.12	4.42	3.53	0.46	8.51		

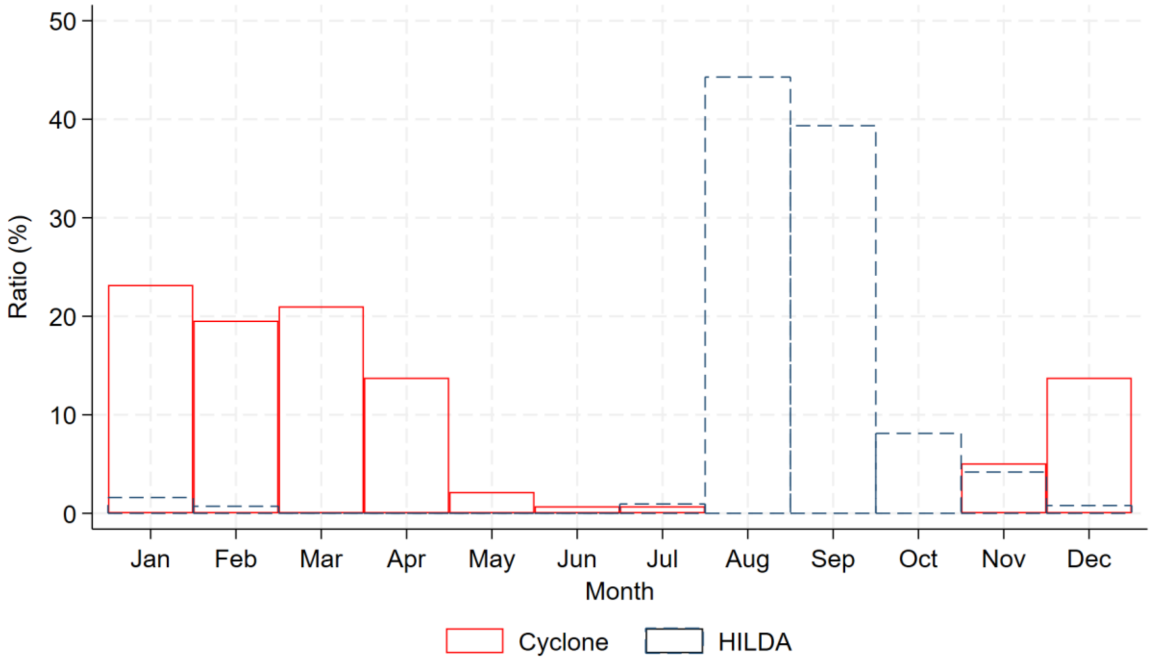
Notes: The results presented in each column and panel are based on a separate FE regression. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Other explanatory variables include age (and its square), marital status, education, household size, 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.

Appendix Figure A1: Tropical cyclone hit map between 2000 and 2023



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

Appendix Figure A2: Distribution of cyclone occurrence and HILDA interview dates



Notes: Data from historical tropical cyclone observed from 2011 to November 2023 and HILDA Release 22 (from Wave 12 onwards).