Natural disasters and the demand for health insurance

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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 reveal that only the most severe category 5 cyclones significantly increase the likelihood of individuals acquiring PHI in both the concurrent and subsequent years. Furthermore, the effect diminishes as the distance from the cyclone's eye increases. The largest estimated cumulated impact amounts to over 5 percentage points, representing approximately 11% 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 and three randomization examinations. Moreover, the cyclone impacts are more pronounced for younger demographics, individuals of higher socioeconomic status, and inhabitants of coastal or historically cyclone-affected areas. Additionally, after ruling out income, transfers, health status, and premiums as mechanisms, our study furnishes suggestive evidence that cyclone-induced home damage and heightened psychological stress are plausible pathways 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 damage. 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).

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 (Gallagher 2014; Wagner 2022), 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 Australian studies have delved into the relationship between natural disasters and PHI enrolment, which constitutes the primary focus of our investigation.

[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 2024d), economic growth (Hsiang & Jina 2014), income (Gallagher & Hartley 2017; Deryugina *et al.* 2018; Groen *et al.* 2020), health (Currie & Rossin-Slater 2013; Bakkensen & Mendelsohn 2016), and mortality (Deryugina & Molitor 2020; Parks *et al.* 2021; Huang *et al.* 2023; Parks *et al.* 2023).

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 important ways to the existing literature.

Firstly, our research pioneers a comprehensive analysis of cyclone effects on PHI demand within the unique context of Australia. This study builds upon the work of Nguyen and Mitrou (2024d), which employed the same dataset and a similar empirical model to specifically analyse residential responses—such as migration and residential insurance—in the context of cyclones in Australia. It also differentiates itself from two subsequent Australian studies that explore the effects of natural disasters and weather-related home damage on life satisfaction (Nguyen & Mitrou 2024a) and locus of control (Nguyen & Mitrou 2024c). However, none of these Australian studies have examined the effects of natural disasters on PHI, which is the focus of the present study. In this regard, along with two US studies that investigate the effects of natural disasters on life insurance (Fier & Carson 2015) and health insurance (Barnes *et al.* 2023), this study contributes to expanding the research on the impacts of natural disasters on health-related insurance uptake.

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 for all Australians regardless of income or wealth (see Duckett and Nemet (2019) for an excellent review of Australian PHI policies). However, Medicare is supplemented by optional PHI, which offers additional benefits and flexibility of health care over what is available via Medicare, including the potential for reduced wait times for elective medical procedures. PHI enrolment is encouraged by the Australian Government as way of reducing financial and service capacity pressure on the publicly funded health system. Despite the implementation of various policies aimed at increasing PHI uptake, the coverage rate has remained relatively low, fluctuating around 45% over the past decade (see Appendix Figure A1). A more nuanced understanding of the factors influencing PHI enrolment could inform the development of policies aimed at enhancing insurance uptake.

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). Similar to Australia, many other high-income countries—including Canada, France, Germany, Japan, the Netherlands, New Zealand, Singapore, South Korea, Sweden, Switzerland, and the United Kingdom (WHO 2010)—maintain mixed healthcare systems. These systems provide citizens with access to essential healthcare services while offering the option to purchase additional private coverage for enhanced benefits. As documented by Hsiang and Jina (2014), several of these countries, including Canada, France, Japan, New Zealand, Singapore, and South Korea, have historically been affected by cyclones. Our findings are particularly relevant to these nations, which share similar health systems and are prone to cyclonic events.

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 (FE) model, effectively controlling for unobservable individual time-invariant factors (Dell *et al.* 2014; Hsiang & Kopp 2018). 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

Additionally, our study innovatively utilizes various cyclone exposure metrics which are identified exogenously by combining the distance from the individual's residing postcode centroid to the eye of the cyclone and the cyclone category. Previous US studies by Fier and Carson (2015) and Barnes *et al.* (2023) relied on natural disaster measures dependent on human behaviours, which may confound the disaster estimates (Hsiang & Jina 2014; Guiteras *et al.* 2015; Botzen *et al.* 2019).[3] Our approach addresses such a concern. We further consolidate our empirical model by applying these exogenously identified measures within an individual FE 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 FE regression model, this study elucidates four principal findings. Firstly, our analysis reveals that both recent and more historical cyclone events, notably those characterized by heightened severity and closer proximity, significantly escalate the acquisition of PHI. Furthermore, the effects are highly non-linear, as only exposure to the most severe category 5 cyclones, with maximum wind speeds exceeding 199 km/h, has a statistically significant impact on PHI uptake. The most substantial estimated impact, amounting to 5.64 percentage points, closely mirrors — and in some cases exceeds — the effects observed with certain policies aimed at augmenting PHI enrolment rates within Australia. Secondly, our

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.

[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.

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, as well as randomization tests.

Thirdly, our extensive heterogeneity analyses unveil nuanced variations in this coping strategy contingent upon cyclone severity and diverse individual, household, and locality characteristics. Specifically, the propensity to adopt this mitigation strategy is strongly influenced by cyclone severity, with individuals responding exclusively to the most severe Category 5 cyclones. Additionally, the analysis exposes a predilection among individuals possessing specific traits, including younger individuals, healthier individuals, renters, affluent individuals, those with prior residential insurance coverage, and residents of coastal or historically cyclone-exposed regions, to procure PHI in reaction to cyclonic events.

Lastly, we find that PHI enrolment is associated with increased subsequent healthcare utilization, particularly in services not covered by the public health system. Moreover, this study offers suggestive evidence that income, transfers, health status, and premiums are unlikely to explain the observed increase in PHI uptake. Instead, cyclone-induced home damage and heightened psychological stress—reflected in a diminished sense of control over life outcomes and lower satisfaction with health and personal safety—emerge as plausible mechanisms through which cyclone exposure influences PHI enrolment.

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 (refer to the user manual by Summerfield *et al.* (2023) for details). This longitudinal survey initially encompasses 7,682 households and over 19,000 individuals, tracking individuals aged 15 years and above within private households annually. The response rate for this initial sample is relatively high, at 66% for in-scope households and 92.3% for enumerated individuals, both measured in Wave 1. In Wave 11 (surveyed in 2011), to retain cross-sectional representativeness, an additional 2,153 households were added to the sample as part of a general top-up. The HILDA survey furnishes comprehensive individual and household-level data, including residential details, health indicators, and labour market engagements.

A notable advantage of HILDA is its ability to track individuals who relocate, thereby maintaining the national representative sample and allowing for observations both pre- and post-cyclone events. This feature facilitates the application of an individual FE 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.

Integrating these datasets involves matching the cyclone's trajectory and timing from the historical cyclone database with the individual's residential postcode centroid and interview date from HILDA. We utilize the restricted version of HILDA, which contains postcodes, as they provide the highest level of geographical granularity available.[4] According to the 2011 census, each postcode area contains, on average, approximately 8,500 people, distributed across around 2,500 postcodes. Appendix Figure A3 illustrates the boundaries of all postcodes in Australia.

2.2. Cyclone exposure measures

Following the approach outlined by Nguyen and Mitrou (2024d), 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 residing 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 international studies (Currie & Rossin-Slater 2013; Henry *et al.* 2020), utilizes a 100 km distance threshold to evaluate exposure and damage patterns across different impact zones.[5] In our baseline analysis, we focus on this distance cutoff to maintain the manageability of the

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[4] Unlike the "General" HILDA dataset, which lacks detailed geographic information, access to the "Restricted" HILDA dataset requires a special application due to the inclusion of more granular geographic identifiers. However, the postcode, as the finest geographical identifier in HILDA, lacks the idiosyncratic geographic detail required to explore the impacts of other natural disasters, such as floods or storm surge. To link HILDA data to satellite data, as has been done for surveys in other countries (e.g., Guiteras *et al.* (2015)), a more precise geographic identifier, such as geocoded household addresses, is required. Consequently, a comprehensive analysis of the impacts of other natural disasters is deferred to future research.

[5] Our approach to measuring cyclone exposure based on the distance to the cyclone eye is closely aligned with the methodology used in earlier US research by Currie and Rossin-Slater (2013). Specifically, in their main specification, Currie and Rossin-Slater (2013) classify an individual as affected by a cyclone if they reside within 30 km of the cyclone's path. In an extended analysis, they account for both the distance to the cyclone eye and the maximum wind speed of each cyclone, interacting the maximum wind speed with indicators for varying distance radii. Our modelling approach aligns with their extended model. Additionally, we build on their method by conducting separate regressions for each distance radius. Similar to the cyclone exposure measures used by Currie and Rossin-Slater (2013), our measures do not account for the typical weakening of cyclones as they move inland. To address the variation in wind speed over a cyclone's trajectory, we could assign the maximum wind speed recorded when the cyclone eye is closest to the centroid of the individual's residential postcode and within a specified distance threshold. However, this alternative approach does not account for the overall maximum wind speed of each cyclone. Similar to Currie and Rossin-Slater (2013), we chose not to adopt this method to maintain computational feasibility and ensure traceability of results. Additionally, we have opted not to employ more complex wind field models, which would necessitate data not available in our current dataset (e.g., cyclone eye radius), reserving this approach for future research.

results and ensure a sufficiently large sample of affected individuals for a robust analysis. In subsequent analyses, we will explore alternative distance cutoffs.

Additionally, drawing from prior research (Hsiang & Narita 2012; Hsiang & Jina 2014), 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).[6] 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.

We utilize these cutoffs to facilitate an intuitive interpretation of our results, as this cyclone category scale is employed by the Australian BOM and is, therefore, more familiar to Australians than other cutoffs (BOM 2024). Moreover, as demonstrated in Appendix Figure A6, which illustrates the distribution of wind speeds for all cyclones affecting individuals in our sample, this categorization results in fairly equal and substantially large subgroups of individuals affected by each cyclone category, thereby enabling reliable estimates of the impact of each category. Importantly, as highlighted by Hsiang and Jina (2014), the use of wind speed cutoffs enables us to examine the potential non-linear effects of wind speed in a more flexible manner. This approach offers an advantage over methods that impose a predetermined functional form—such as a continuous specification, logarithmic transformation, or quadratic terms—on the relationship between wind speed and PHI enrolment.

Several international studies have effectively employed wind speed thresholds, albeit with different cutoffs, to examine the potential non-linear impacts of cyclones on various socio-economic outcomes (Anttila-Hughes & Hsiang 2013; Deryugina 2017; Franklin & Labonne

[6] While this approach efficiently manages a large number of cyclone exposure variables and aligns with data availability constraints, it does not account for other co-occurring and currently unobserved hazards, such as torrential rain, flooding, and storm surge. This method has been widely adopted in previous international studies, potentially for similar reasons (Currie & Rossin-Slater 2013; Hsiang & Jina 2014; Franklin & Labonne 2019; Parks *et al.* 2021).

2019; Henry *et al.* 2020; Parks *et al.* 2021; Huang *et al.* 2023). In the subsequent sections, we will further explore the potential non-linear effects of wind speed by utilizing alternative cutoffs and applying different functional forms for wind speed.

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," as will be explained in more detail below. In Australia, the financial year runs from 1st July of one calendar year to 30th June of the following calendar year. During our study period (2011-2023), the majority of HILDA interviews (92%) were conducted between August and October (see Appendix Figure A5), while 96% of cyclones, across all categories, occurred between November and April. This temporal alignment suggests that our measure of cyclone exposure effectively captures the concurrent impact of local cyclones on PHI coverage, as both are recorded within the preceding 12 months. To account for differences in survey timing across individuals in the same postcode within the same survey wave, our empirical models will include controls for survey month or survey week dummies. Additionally, we will investigate the potential attenuated or deferred effects of cyclones by incorporating lagged cyclone exposure variables alongside the concurrent cyclone exposure measure in the regression analysis of current PHI enrolment.

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 three main reasons. Firstly, it represents the predominant form of PHI in Australia and is the 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,[7] 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 is 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).[8] 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.

Thirdly, using this PPHC measure reveals that 50% of the individuals in our final sample are identified as covered by PHI for the purposes of this study (see Appendix Table A1 for variable descriptions and summary statistics). It is important to highlight that this coverage rate closely aligns with the rate derived from the same PHI measure and administrative data for the same period, as reported in Appendix Figure A1. This consistency between HILDA and administrative data sources, reaffirming a previous validation study by Nguyen *et al.* (2023), suggests that the self-reported measure of PHI coverage in HILDA is sufficiently reliable to detect any significant changes in the demand for PHI in response to local cyclones.

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[7] 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.

[8] For instance, policies like the Lifetime Health Cover (LHC) and the Medicare Levy Surcharge (MLS) penalize individuals who do not hold PPHC under certain circumstances (Duckett & Nemet 2019). While there is no formal requirement for individuals to hold coverage for the entire financial year, various policies encourage continuous enrolment. Specifically, the LHC loading and the MLS provide strong incentives for individuals to remain insured once they have enrolled, leading to a tendency for policyholders to retain their insurance throughout the year.

2.4. Sample

Our primary unit of analysis is the individual, primarily due to the individual-level measurement of PPHC. 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 FE 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 A2 illustrates the geographic distribution of cyclone 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 over 110,000 individual-year observations derived from more than 15,000 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 used in previous studies that explore the effects of natural disasters using individual- or household-level panel survey data (Henry *et al.* 2020; Nguyen & Mitrou 2024d),[9] we employ an individual FE model to examine the effects of cyclones on outcome Y for individual i, residing in postcode j, at time t:

[9] We employ an individual-level regression model and, therefore, refrain from using a model based on aggregated data, such as a postcode-level regression, for five main reasons. First, as discussed further below, both the outcome variable and the treatment in this study are measured at the individual level. This is important because exposure to the same cyclone can vary even among individuals residing in the same postcode due to differences in survey timing within a single wave. Second, the individual FE model allows us to control for unobservable, time-invariant

$$Y_{ijt} = \alpha + \sum_{L=0}^{k} [Z_{ij(t-L)}\beta_L] + X_{ijt}\gamma + m_{it} + \lambda_t + \delta_i + \varepsilon_{ijt} \tag{1}$$

Here, Z_{ijt} is a categorical variable denoting whether the individual i experienced a cyclone of category 1, 2, 3, 4 or 5 (with unaffected individuals serving as the reference group) in the 12 months preceding the survey. X_{ijt} represents a set of time-variant explanatory variables. m_{it} denotes interview month indicators, while λ_t describes survey year dummy variables. δ_i accounts for individual time-invariant unobservable factors, and ε_{ijt} denotes the idiosyncratic error term.

In the distributed lag model (1), we initially examine the contemporaneous effect of cyclone exposure on an individual's PHI enrolment (i.e., when $L = 0$). We then investigate potential delayed effects by incorporating k lags of cyclone exposure, along with the current exposure, in the regression of current PHI uptake. The optimal lag length k will be empirically determined based on the data and the applied models. In Equation (1), α, β_L and γ are parameters to be estimated, with β_L serving as our vector of parameters of interest.

To mitigate potential confounding effects, we incorporate a limited number of individual and household-level time-variant variables into X_{ijt}. These variables include the individual's age (and its square), marital status, education level, household size and major city residency. As noted above, we also address temporal disparities in outcomes by including dummy variables for survey month and year separately. To address concerns about potential correlations between cyclone exposure, outcomes, and unobserved time-invariant factors at the postcode level, we

individual characteristics that may be associated with both cyclone exposure and PHI enrolment—controls that a postcode-level FE model cannot provide. Third, this micro-econometric approach has been widely used in international studies that employ individual- or household-level data to assess the effects of natural disaster exposure at more aggregated spatial levels, such as zip codes, districts, or cities (Anttila-Hughes & Hsiang 2013; Deryugina *et al.* 2018; Franklin & Labonne 2019; Groen *et al.* 2020; Henry *et al.* 2020). Fourth, a postcode-level FE model cannot account for compositional changes driven by cyclone-induced relocation. Finally, while the HILDA survey is nationally representative, it may not be geographically representative at a finer spatial scale, such as the postcode level (Summerfield *et al.* 2023).

control for postcode fixed effects in Equation (1). Incorporating postcode fixed effects is crucial to our study, which relies on postcode boundaries to measure the distance between individuals' residential postcode centroids and the cyclone path. As illustrated in Appendix Figure A3, postcode boundaries in Australia vary significantly in size and distribution. Relying on postcode centroids alone could inaccurately capture households' proximity to cyclone paths. By controlling for postcode fixed effects, we mitigate this concern in our empirical model. Furthermore, we consider local socio-economic contexts that may influence individual behaviours by incorporating regional unemployment rates and Socio-Economic Indexes for Areas (SEIFA).

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 (see Appendix Figure A4 for a graphical representation of selected cyclones and their corresponding affected postcodes).[10]

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

[10] For demonstration purposes, we utilize the 2006 postcode boundaries, as this is the earliest shapefile package publicly available from the Australian Bureau of Statistics' website. It is important to note that the individual's residential postcode centroid, which cannot be disclosed due to confidentiality requirements, is used to link with the cyclone's eye path. For illustrative clarity, five cyclones of varying categories that made landfall during the study period are selected for presentation in Appendix Figure A4.

same postcode may experience differing cyclone exposures to the same cyclone within the same survey year (refer to Appendix Figure A5 for the distribution of survey and cyclone timing). To address potential serial correlation issues, we cluster standard errors at the postcode level (Cameron & Miller 2015). In robustness checks, we also present results with standard errors clustered at the individual level or without 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 concurrent cyclone exposure status. Merely 6% 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. The table shows that 7,221 year-observations, corresponding to 5,653 distinct individuals, are categorized as "treated," providing a sufficiently robust sample size for capturing cyclone effects effectively. Most affected individuals are observed both before and after a cyclonic event, and one-third of them were exposed to more than one cyclone over the 11-year study period. Among the "treated" individuals, 32.72%, 9.38%, 6.84%, 38.55%, and 12.51% were affected by at least one cyclone of category 1, 2, 3, 4, and 5, respectively. Appendix Table A1 reports significant standard deviations in both cyclone exposure measures and the outcome variable, both between and within individuals. This variation is sufficiently substantial to support the application of an individual FE model to examine the impact of cyclones.

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 area 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 (Column 1) underscore significant contemporaneous impacts of cyclones on the likelihood of individuals having PPHC. Specifically, the positive and highly statistically significant estimate for current exposure to category 5 cyclones ($p < 0.01$) indicates that individuals affected by any category 5 cyclone are 2.82 percentage points (pp) more likely to have PPHC compared to unaffected individuals. However, the effect of cyclone exposure is statistically significant only for category 5 cyclones, as the estimates for other categories, also reported in Column 1, are not statistically significant.

Acknowledging the time delay involved before observable changes in insurance behaviours post-cyclones (Kousky 2019; Kraehnert *et al.* 2021; Nguyen & Mitrou 2024d), we investigate the dynamic effects of cyclones on health insurance enrolment decisions. To address this temporal aspect, we first introduce an additional categorical variable in Equation (1) to represent exposure to cyclones one year prior to the assessment of the PPHC outcome. The estimates for both concurrent and one-year lagged cyclone exposure are delineated in Column 2 of Table 2. Notably, the results for contemporaneous cyclone exposure closely align with the baseline findings in Column 1, further reinforcing our previous conclusions. Moreover, consistent with observed trends in the immediate aftermath of cyclones, the estimates indicate that only the most severe category 5 cyclones have a statistically significant ($p < 0.01$) effect on future PPHC acquisition. Specifically, individuals residing within 100 km of the path of a category 5 cyclone in the previous year are 2.54 pp more likely to hold PPHC in the subsequent survey wave.

Column 3 of Table 2 shows little evidence of a deferred cyclone effect beyond the two-year period, as the estimates for two-year lagged exposure variables are not statistically significant. Notably, with the exception of a negative and statistically significant ($p<0.01$) estimate for exposure to category 4 cyclones within 100 km of the eye on current PPHC, all other estimates—including those for category 5 cyclones—are not statistically significant. Importantly, the inclusion of two-year lagged cyclone exposure variables does not significantly alter the estimates for current and one-year lagged exposure, as the positive and statistically significant effects remain exclusive to category 5 cyclones.

Similarly, the estimates for current and one-year lagged category 5 cyclones closely resemble those from the one-year distributed lag regression, as presented in Column 2, when we incorporate both one-year lagged and lead (one year future) cyclone exposures into the Equation (1). This reinforces the robustness of our findings. The results from this specification, reported in Column 4, further indicate that, with the exception of a somewhat unexpected positive and statistically significant estimate ($p < 0.01$) for one-year lead exposure to a category 4 cyclone,[11] the estimates for all other variables capturing future cyclones, including category 5 cyclones, are not statistically significant at any conventional level.[12] The outcomes of this

[11] The observed positive correlation between one-year lead exposure to a category 4 cyclone and the probability of obtaining PPHC in the current year is intriguing and warrants further consideration. One plausible explanation is that cyclones tend to be highly spatially correlated over time (Hsiang & Jina 2014), and individuals may have, by chance, accurately anticipated the arrival of future cyclones and purchased PPHC in advance. While this finding is unexpected, it highlights the potential importance of improved weather forecasting and its role in shaping individual behaviour (Morss *et al.* 2017; Millet *et al.* 2020). Future research could delve deeper into this pattern, particularly by exploring whether advancements in forecasting technology enhance individuals' ability to anticipate cyclones. Such investigations would benefit from more comprehensive datasets or improved methodological approaches beyond those currently available.

[12] We opt not to use this model as our primary model because, although including the lead exposure does not significantly alter the findings, it reduces the sample size by approximately 15%.

placebo test affirm the exogeneity of cyclones and validate our ability to isolate their causal impact on health insurance demand.

The empirical results thus far demonstrate that exposure to only the most severe category 5 cyclones, with maximum wind speeds exceeding 199 km/h, has a statistically significant impact on PPHC uptake. This finding suggests a highly non-linear relationship between cyclone maximum wind speed and PPHC enrolment. This finding, which will be further validated in Section 5, aligns with Nordhaus (2010), who found that the macroeconomic impact of US hurricanes is also highly non-linear, with catastrophic effects occurring above a certain wind speed threshold. This evidence is further supported by recent Australian studies, which identified that the impacts of cyclones on migration and wellbeing are concentrated among cyclones with exceptionally high wind speeds (Nguyen & Mitrou 2024d, a). Moreover, our finding of a short-lived impact of cyclones on PHI enrolment is consistent with that of a US study by Gallagher (2014), which observed a surge in residential insurance uptake in the year following a flood but subsequently returned to baseline levels.

For the sake of conciseness and clarity, unless otherwise specified, the remainder of this paper will focus on the results using exposure to any category 5 cyclone within 100 km of the cyclone's eye as the primary measure of cyclone exposure. Specifically, the categorical variable Z_{ijt} in Equation (1) is replaced by a binary variable indicating whether an individual was affected by a category 5 cyclone. Additionally, we include both current and one-year lagged measures of this exposure, as only this most severe category has demonstrated a statistically significant, albeit short-lived, deferred impact on PPHC uptake. Furthermore, we report the cumulative effects of this cyclone exposure.[13]

[13] Numerically, the cumulative effect of cyclone exposure from the one-year distributed lag regression (i.e., $L = 1$ in Equation (1)) is the sum of the concurrent and one-year lagged cyclone estimates. However, as detailed in Wooldridge (2003, Chapters 10 and 11), for inferential purposes, the estimate of this cumulative effect and its standard error can be obtained from a transformed regression. This transformed model is derived by replacing the

Column 6 in Table 2 illustrates the cumulative impact of exposure to a category 5 cyclone on current PPHC enrolment as obtained from the transformed regression model (i.e. Equation (2)). The estimate reveals a cumulative effect of 5.29 pp, which is statistically significant at the 1% level. As anticipated, this cumulative estimate is equal to the sum of the estimates for current exposure and exposure lagged by one year to a category 5 cyclone, as obtained from the baseline regression specified in Equation (1) and reported in Column 5 of Table 2.

5. Robustness checks

5.1. Sample attrition issues

A potential concern in this study design is the influence of cyclone exposure on participant retention. To address this, an individual FE model, analogous to Equation (1), is employed. The primary dependent variable indicates whether an individual was not interviewed in the subsequent survey wave, with an additional variable introduced to identify death as the reason for non-interview. Explanatory variables include current and one-year lagged indicators of cyclone exposure within a 100-km radius, alongside other time-varying covariates specified in Equation (1). The sample is restricted to individuals residing in regions affected by at least one cyclone during the study period.

Results from this exercise, presented in Appendix Table A2, indicate that, consistent with the sampling statistics for the entire HILDA survey presented by Summerfield *et al.* (2023), the overall attrition rate in our sample is relatively low at 6.25%. Moreover, regression results reveal statistically significant associations between certain demographic characteristics,

one-year lagged cyclone exposure variable ($Z_{ij(t-1)}$) in the baseline one-year distributed lag regression with a new variable, calculated as ($Z_{ij(t-1)} - Z_{ijt}$). Specifically, the following transformed regression model is used:

$$Y_{ijt} = \Omega + \theta Z_{ijt} + \xi(Z_{ij(t-1)} - Z_{ijt}) + X_{ijt}\pi + m_{it} + \lambda_t + \delta_i + \eta_{ijt} \qquad (2)$$

In Equation (2), η_{ijt} represents the error term, and Ω, θ, ξ, and π are parameters to be estimated. Other variables are defined as in Equation (1). The estimate of Z_{ijt} from Equation (2), denoted as $\hat{\theta}$, captures the cumulative effect and its standard error. All cumulative effects reported in this paper are calculated based on this transformed regression model.

notably age and education, and the probability of non-interview, contingent upon the specific reason for attrition. However, the overall explanatory power of the model is limited, as indicated by the maximum R-squared value of 0.02. Crucially, estimates for current and lagged cyclone exposure variables are jointly statistically insignificant, with Wald test p-values exceeding 0.10.[14] Overall, these findings alleviate concerns regarding potential cyclone-induced sample selection bias.

5.2. Testing for non-linearity in wind speed effects

This sub-section further investigates potential non-linearities in the effects of wind speed by applying various functional forms and cutoffs. First, wind speed is linearly included as a continuous variable, replacing the five-category wind speed variable used in the baseline regression. Since wind speed is not observed for individuals unaffected by cyclones, an arbitrary value of one is assigned for these individuals.[15] In this regression, as well as in all subsequent regressions using this derived wind speed variable, we also include a binary variable indicating whether an individual was unaffected by a cyclone.

Second, to explore non-linearity in the effects of wind speed further, we introduce the derived wind speed variable in logarithmic, quadratic, and cubic forms. Third, we include a dummy variable indicating whether an individual was affected by a cyclone of any category. Fourth, rather than using the wind speed cutoffs suggested by the BOM, we implement an alternative approach that categorizes observed wind speeds into four groups, each separated by 50 km/h increments. For clarity and conciseness, this sub-section employs a 100 km distance threshold

[14] Our finding of a statistically insignificant effect of cyclone exposure on attrition due to death contrasts with previous evidence of a substantial impact of cyclones on mortality both globally (Huang *et al.* 2023) and in the US (Parks *et al.* 2022; Parks *et al.* 2023; Young & Hsiang 2024). These discrepancies may be attributed to differences in data, empirical models, and research contexts.

[15] It is important to note that the estimate for this derived wind speed variable remains consistent even when alternative values, such as zero or the mean wind speed of all cyclones in the sample, are used in place of one (Wooldridge 2010).

to identify individuals affected by a cyclone and includes both current and one-year lagged measures of cyclone exposure in the modified individual FE model.

The estimate of current wind speed, presented in continuous form in Column 1 of Appendix Table A3, is positive and statistically significant at the 1% level. This result from the linear specification suggests that, among individuals affected by any cyclone, a one km/h increase in wind speed is associated with a 0.02 pp increase in PPHC uptake. In contrast, the estimate for lagged wind speed from this specification (also reported in Column 1) is considerably smaller in both magnitude and statistical significance; it is approximately half the size of the current wind speed estimate and statistically insignificant.

Column 2 of Appendix Table A3 shows that only the estimate of current wind speed in its logarithmic form is statistically significant at the 1% level. The positive and statistically significant estimate of logarithmic current wind speed indicates a positive non-linear relationship between wind speed and PPHC enrolment among individuals affected by cyclones. Intuitively, this estimate suggests that higher wind speeds are associated with increased PPHC enrolment; however, the marginal impact of wind speed diminishes as wind speed increases. Furthermore, the statistically insignificant estimate of lagged logarithmic wind speed indicates no delayed effects of cyclones on PPHC enrolment.

There is limited evidence of non-linearity in the regressions using quadratic or cubic forms of wind speed (Columns 3 and 4, respectively), as most wind speed variables in these specifications are statistically insignificant at conventional levels, indicating no significant impact of wind speed on PPHC uptake. Similarly, when using the binary variable to indicate whether an individual was affected by a cyclone, regardless of the observed wind speed (Column 5), no statistically significant effect is found for either current or lagged forms on PPHC enrolment.

The lack of statistical significance, particularly for estimates related to past cyclones, along with certain contradictory results in regressions using pre-specified functional forms of wind speed, supports the use of a more flexible five-category wind speed variable in the main regression. Additionally, using an alternative cutoff that categorizes wind speeds into four groups separated by 50 km/h increments further confirms that only cyclones with the highest wind speeds (i.e., 200 km/h or higher), whether recorded concurrently or in the previous year, have a statistically significant effect on increasing PHI uptake. Overall, these robustness checks reinforce our primary finding that the effects of cyclones on PHI enrolment are only significant for the most severe cyclones, specifically those in category 5. As previously mentioned, our finding of highly non-linear impacts of wind speed is consistent with results from other studies (Nordhaus 2010; Nguyen & Mitrou 2024d, a).

5.3. Other robustness checks

To enhance the robustness of our findings, we conducted a series of sampling and specification tests. For conciseness, we present the results using exposure to any category 5 cyclone within 100 km of the cyclone's eye as the primary measure of cyclone exposure, as only this most severe category has been shown to statistically significantly impact PPHC enrolment. Additionally, we include both current and one-year lagged measures of this exposure, given that the earlier results indicate their statistically significant effect on current PPHC uptake. We deliberately report the estimates for current and lagged cyclone exposure separately in this section to illuminate potential mechanisms preceding the cyclone's impacts.

Our initial sampling test involved including all individuals observed in the entire dataset. Results from this larger sample, detailed in Table 3 - Panel A - Column 2 are closely aligned with the baseline results (reiterated in Panel A - Column 1), albeit with slightly smaller magnitude (a cumulative effect of 4.91 pp compared to 5.29 pp in the baseline). We additionally performed an experiment wherein individuals who relocated between adjacent survey waves

—representing approximately 15% of the total population— 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 2024d). The resulting estimates, presented in Panel A - Column 3, closely align with the baseline estimates.

In contrast, the estimates derived from a regression based on the sample of individuals who relocated between adjacent survey waves ("movers") show much weaker statistical significance (Panel A - Column 4). Specifically, the estimate for current cyclone exposure is only statistically significant at the 10%, while the estimate for lagged cyclone exposure is no longer statistically significant. These results, partly due to the relatively smaller sample size, suggest that the effects of cyclones are most pronounced for individuals who remain in place ("stayers"). When considered alongside previous Australian evidence of relocation following exposure to severe cyclones (Nguyen & Mitrou 2024d), these findings imply that migration may serve as a mitigating strategy for cyclone-affected individuals to lessen the adverse effects of future cyclone exposure.

We proceed to assess the robustness of our findings through a series of specification checks. Initially, we exclude postcode dummies from our individual FE regression (results in Panel A - Column 5). Additionally, we cluster the estimates at the individual level rather than the postcode 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) linear model (Panel A - Column 8).[16]

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

[16] To address potential confounding effects, we included time-invariant variables, such as gender and migration status, in these specifications.

by cyclone events. Alternatively, we introduce a one-year lag of these time-variant variables into the current PPHC regression to address concerns regarding potential endogeneity (Panel A – Column 10).[17] Conversely, we additionally and separately control for each of several other time-variant variables which may have been concurrently affected by cyclones. The first time-variant variable is the local PHI premium, which is calculated by averaging all positive expenditures on PHI reported by individuals, excluding the individual in question, residing in the same Local Government Area (LGA) in the HILDA dataset for a given survey year.[18] Other time-varying 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, SF36 mental health summary, and health satisfaction. Estimates from these robustness checks are reported in Panel A – Column 11 (for the inclusion of the LGA PHI premium) and Panel B - Columns 1 to 9 (for other individual-level variables, respectively). Additionally, we account for differences in survey timing by controlling for week-of-year fixed effects, instead of month-of-year fixed effects used in the baseline regression (Panel B - Column 10). Finally, we apply an RE logit model,[19] acknowledging the binary nature of the PPHC status (Panel B - Column 11).

[17] However, we do not adopt this modified model as our primary specification due to the reduction in sample size caused by the inclusion of lagged variables. Moreover, the estimates of these lagged variables, which are not intended to be interpreted causally, fall outside the primary focus of this study.

[18] As of 2024, there are a total of 566 LGAs in Australia. Information on household expenditure on PHI premiums is available from Wave 5 onwards and is provided by all surveyed members who self-identified as having responsibility for paying household bills. In cases where multiple members of the same household provided responses (approximately one-quarter of all surveyed households), the household expenditure amount is averaged across all individuals who responded. Furthermore, expenditure is measured at the household level and is reported on an annual basis. Although there are some concerns regarding the quality of the expenditure data reported in HILDA, household expenditure measures have been utilized in previous studies (Mitrou *et al.* 2024; Nguyen & Mitrou 2024d). We refrain from using PHI premiums as the main outcome variable because they are only available at the household level, contain a significant amount of missing data, and may be more susceptible to reporting errors (Nguyen *et al.* 2023). Refer to Appendix Figure A1 for a time series of annual household expenditure on PHI. Unreported results indicate that the estimate for the LGA PHI premium is not statistically significant at any conventional level.

[19] A FE logit model failed to converge, likely due to the relatively large sample size and the extensive use of dummy variables. For the same reason, an RE logit model controlling for postcode fixed effects also failed to converge, so we conducted a robustness check using an RE logit model without controlling for postcode fixed

Throughout these 18 specification tests, our findings demonstrate resilience to alterations in model specifications and estimation methodologies. A notable exception is the pooled OLS estimates, which remain highly statistically significant ($p<0.01$) but show a larger magnitude, with the cumulative effect being 22% greater in the pooled OLS regression. This significant increase in magnitude, when considered alongside the result for a Hausman test (F-statistic unreported), confirms strong correlation within individual error terms, further supporting the use of an individual FE model.

5.4. Randomization tests

To further validate the robustness of our results against potential mis-specification concerns, which could lead to spurious or biased estimates, we conduct three variations of a randomization exercise, following the approach outlined by Hsiang and Jina (2014).[20] In the first randomization approach, termed "whole sample", we randomly assign cyclone exposure observations across the entire sample. In the second approach, called "between individuals", we randomly reassign each individual's cyclone exposure history to another individual while preserving the timing of cyclone exposure. This method maintains the chronological order of years and tests whether regional trends could generate spurious correlations. Lastly, in the third variation, denoted "within individual", we randomly reassign the timing of cyclone exposure

effects. As detailed earlier, we accounted for numerous time-invariant variables in this RE regression. Additionally, we present the estimates in marginal effects after logit regressions to ensure comparability with those in the baseline regression. We refrain from using a logit model as the main specification for three key reasons. First, the individual FE logit model failed to converge in our case. Second, a linear OLS model is considered suitable for binary dependent variables when the mean value is approximately midway between zero and one (Wooldridge 2010). In our case, the mean value is 0.5, aligning with this criterion. Third, running a RE logit regression takes substantially more time than a linear individual FE OLS model.

[20] We utilize the Stata command *rndm*, developed by Hsiang and Jina (2014), to implement these randomization procedures. In this experiment, we apply Equation (2), which captures the cumulative impacts of current and one-year lagged exposure to any category 5 cyclone within 100 km on current PPHC enrolment, with one modification. Specifically, we exclude postcode fixed effects to reduce the computational time required for this process, which involves 3,000 replications across three randomization variations. As shown above, while including postcode fixed effects in the individual FE model does not change the results, it significantly increases the running time. Instead, we incorporate state/territory fixed effects in this experiment. We thank an anonymous reviewer for their suggestion to employ these tests, which further bolstered our findings.

within each individual, altering only the temporal structure of the data to examine whether time-invariant cross-sectional patterns across individuals might produce spurious correlations.

The results for specifications based on Equation (2), with 1,000 replications, are presented in Figure 1. From this figure, we can draw two key conclusions. First, the false treatment effects are centred around a mean value of zero, indicating that the model specified in Equation (2) is unlikely to generate biased results. Second, the coefficients from the estimates using actual data, represented by the solid red line, are located on the right-hand side of the distribution, with p-values < 0.01 in all cases.[21] This exercise reinforces the credibility of our findings, suggesting that the observed results are unlikely to have occurred by chance.

5.5. Impacts of cyclone by distance to the cyclone's eye

We further validate our findings by analysing the differential impacts of cyclones based on their proximity to the cyclone's eye, using three distance bands: within 40 km, between 40 and 100 km, and between 100 and 200 km. In this analysis, as outlined above, we focus on exposure to category 5 cyclones, as only this most severe category has been demonstrated to significantly affect PPHC enrolment. The results, presented in Table 4, indicate that the estimated effects of cyclones on PPHC enrolment substantially diminish as the distance from the cyclone's eye increases. Specifically, the cumulative probability of enrolling in PPHC decreases by 15%—falling from 5.64 pp to 4.77 pp—when comparing individuals residing within 40 km of the cyclone's eye to those situated between 40 and 100 km away from the centre of a category 5 cyclone. Likewise, the likelihood of purchasing PPHC declines by 35%, dropping from 4.77 pp to 3.10 pp, and becomes less statistically significant, with the significance level decreasing from 1% to 5%, when comparing individuals located between 40 and 100 km and those residing

[21] In contrast, Appendix Figure A7 presents randomization tests using exposure to category 1 to 4 cyclones as the treatment, showing that the estimates from actual data are near zero, with false treatment effects centred around zero (all p-values > 0.50). These additional randomization tests further support our earlier finding of no statistically significant effect of exposure to category 1 to 4 cyclones on PPHC uptake.

between 100 and 200 km from the cyclone's eye. These findings highlight the critical roles of geographical proximity in shaping individual responses to such natural disasters.

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

6. Heterogeneous cyclone impacts on private 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 (2024d), we run separate individual FE regression models for each subgroup within distinct groups defined by one of 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").[22]

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),[23]

[22] 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.

[23] Following the methodology outlined by Nguyen and Mitrou (2024d), 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 (2024d), 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

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"). We intentionally focus on historical cyclone exposure, rather than current or projected exposure, to isolate the specific influence of past climatic conditions on the behaviour of current residents. Understanding this relationship is essential for informing preparedness strategies and policy planning for future cyclones, particularly in regions with varying levels of historical exposure (Dell *et al.* 2014; Carleton & Hsiang 2016). Additionally, a 30-year time frame is selected to reflect the long-term climatic patterns of the region, while also facilitating the division of the population into two comparably sized subgroups, thus enabling more robust and reliable group-specific estimates.[24]

For greater clarity and precision, this section consolidates the cyclone exposure measure into a single indicator, representing exposure to either a category 4 or 5 cyclone within a 100 km radius of its eye. This consolidation is motivated by the statistically significant impacts of these

insurance coverage, thereby indicating that households surpassing the $1,250 threshold are likely to be equipped with residential insurance.

[24] As expected, the proportion of individuals from historically cyclone-free areas impacted by any category 4 or 5 cyclone within 100 km of its eye is relatively low, at 0.46%, as shown at the bottom of each panel in Appendix Table A4. In comparison, 6.41% of individuals in historically cyclone-prone areas are affected. The small number of affected individuals in cyclone-free areas may not provide sufficient power to detect statistically significant cyclone effects, and the corresponding estimates should be interpreted with caution. Likewise, the relatively small sample sizes within some subgroups or the limited number of individuals affected within these subgroups may affect our ability to detect statistically significant differences in cyclone impacts across subgroups.

cyclone categories, as shown in Table 2, Column 2. Both current and lagged exposure to category 5 cyclones demonstrate high significance, while current exposure to category 4 cyclones is positive, though not highly statistically significant. This approach ensures an adequate sample size of individuals exposed to these cyclone categories across subpopulations, thereby facilitating a robust heterogeneity analysis.[25] Additionally, as noted earlier, we use Equation (2) to derive the cumulative effects that encompass the full impact of cyclones—both immediate and delayed, though short-lived—on PPHC uptake within this section.

The results of this analysis are graphically represented in Figure 2. Figure 2 illustrates the cumulative estimate for the entire population, which is positive and statistically significant at the 1% level. This indicates that individuals exposed to any category 4 or 5 cyclone within a 100 km radius of its eye are 2.18 pp more likely to acquire PPHC. Notably, this population estimate falls between the impacts of any category 4 cyclone and any category 5 cyclone combined, as reported in Table 2, Column 2. Figure 2 visually represents the regression estimates of cyclone impacts and the numerical sample means of the dependent variable across various subgroups of the population. The figure highlights more pronounced cyclone effects for selected subgroups, where cumulative impacts are either larger in magnitude or more statistically significant.

For example, younger individuals demonstrate a higher likelihood of acquiring PPHC when exposed to category 4 or 5 cyclones within 100 km of the cyclone's eye. This is reflected in an estimated cumulative cyclone impact of 3.63 pp, which is statistically significant ($p < 0.01$) exclusively for the younger group. This significance persists despite their comparatively lower

[25] Appendix Figure A8 presents the results from a heterogeneity analysis, focusing on exposure to remaining category 1 to 3 cyclones within 100 km of their eye. Consistent with the estimated cumulative effects for the whole population—depicted as the dashed horizontal line in the figure—and the baseline results from Table 2, the estimates for all subgroups lack statistical significance. The absence of statistically significant effects for these cyclone categories further supports our earlier conclusion regarding the highly non-linear relationship between cyclone wind speed and its impact on PPHC uptake.

baseline PPHC rates, as indicated by the reported mean values. Similarly, only healthier individuals—who are approximately 13% more likely to have PPHC—show a statistically significant response to the same cyclone, purchasing more coverage.

Figure 2 also illustrates that renters, who have a 50% lower likelihood of possessing PPHC at baseline compared to homeowners (i.e., 31% versus 62%), are statistically significantly ($p < 0.01$) more likely to acquire this form of insurance when exposed to any category 4 or 5 cyclone within a 100 km radius of its eye. In contrast, only individuals from wealthier households, who are approximately 36% more likely to have PPHC at baseline, demonstrate a statistically significant increase ($p < 0.01$) of 3.17 pp in their likelihood of purchasing this type of PHI when faced with a new cyclone event. We also observe from Figure 2 that only individuals with prior residential insurance coverage, who are unexpectedly 30% more likely to have PPHC than those without residential coverage, show a statistically significant ($p < 0.05$) increase of 3.08 pp in their likelihood of purchasing private health insurance.

Subgroup estimates based on proximity to the coastline reveal significant disparities between coastal and inland residents. Notably, individuals in coastal regions have a much higher rate of PPHC, with a mean of 58% compared to 46% for inland area residents. Moreover, only coastal area residents exhibit a significant increase in demand for PPHC when affected by cyclones, as evidenced by statistically significant estimates ($p<0.01$) exclusively for this group. The discovery of a significant cyclone-induced 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). Additionally, 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). It is also likely that residents in coastal regions are wealthier than those in inland regions, and, in line with the finding of a more pronounced cyclone effect for wealthier individuals presented above, are thus more likely to afford PPHC.

Furthermore, individuals residing in historically cyclone-prone regions, who demonstrate a lower likelihood of possessing PPHC at baseline - constituting 51% compared to 53% of those in historically cyclone-free areas - are statistically significantly ($p < 0.05$) more inclined to procure this form of insurance when faced with a new cyclone event. For these individuals, exposure to any category 4 or 5 cyclone within 100 km of its eye results in an increase in PPHC uptake by 2.15 pp. This estimated impact is substantial, accounting for approximately 4% of the sample mean or 11% of the difference in mean coverage between historically cyclone-prone and historically cyclone-free regions.

Our finding of a more pronounced cyclone effect on PPHC uptake among residents of historically cyclone-prone areas aligns with the results of an Australian study by Nguyen and Mitrou (2024d). This study highlights that individuals in cyclone-prone regions demonstrate an increased propensity to acquire residential insurance following new cyclone occurrences. These patterns are consistent with the notion that individuals may base their insurance purchase decisions on the anticipated likelihood of future natural disasters, informed by historical disaster occurrences (Kousky 2019; Kraehnert *et al.* 2021). Additionally, our finding of a heightened cyclone effect on PPHC for residents in cyclone-prone areas—where private hospitals are disproportionately less available compared to cyclone-free areas (Wood *et al.* 2023)—suggests that the availability of healthcare services may not be a contributing factor to the cyclone-induced demand for PHI.[26]

Figure 2 also provides minimal evidence of differential cyclone impacts across subgroups defined by gender or urban residency, as the estimates for these subgroups are statistically

[26] This prediction aligns with the observed pattern of a slightly more pronounced cyclone impact on rural residents. Specifically, Figure 2 and the associated Appendix Table A4 demonstrate that the estimates are somewhat greater and more statistically significant for rural residents. While there is no disproportionate difference in the distribution of public hospitals between rural and urban areas in Australia, private hospitals are concentrated in wealthier and more densely populated regions (Wood *et al.* 2023). This suggests that the supply of healthcare services may not play a significant role in explaining the increased demand for PHI among rural residents following cyclone events.

significant, albeit at varying levels, or are of largely similar magnitude. Overall, the aforementioned heterogeneous analysis underscores that individuals with specific characteristics - such as younger individuals, healthier individuals, renters, wealthier individuals, individuals with prior residential insurance, and residents of coastal or historically cyclone-exposed regions - are more inclined to acquire PHI when affected by cyclones.[27]

The discovery that solely individuals from more socio-economically advantaged backgrounds, as indicated by higher income or better health, exhibit a greater likelihood of obtaining private health insurance, is consistent with the findings of Nguyen and Mitrou (2024d), 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.

[27] Unfortunately, a formal test for differences in coefficient estimates between two separate FE regressions is not readily available in Stata. Statistically significant differences (at the 5% level) between estimates for subgroups can be visually assessed by examining whether the 95% confidence intervals overlap. This visual inspection suggests that the differences in cyclone effects between subgroups are not statistically significant, as the confidence intervals overlap in all cases. However, relying solely on visual inspection or formal testing may be overly conservative, particularly when sample sizes are relatively small or when only one subgroup's estimate is statistically significant. Testing the difference between two estimates where only one is statistically significant may not be meaningful (Wooldridge 2010).
An alternative approach, which allows for a formal test of differences between subgroup estimates, involves estimating a FE model on the pooled sample and including an interaction term between the cyclone exposure variable and the subgroup variable of interest. The statistical significance of the interaction term indicates whether cyclone impacts differ significantly between subgroups. Nevertheless, we opted not to use this approach, as it introduces more restrictive assumptions than our current method. Specifically, it assumes that the effects of other covariates, which are also controlled for in the regression, are identical across subgroups. While this concern could be mitigated by interacting the subgroup variable with all other covariates, our model includes a substantial number of dummy variables, such as postcode and time dummies, which would significantly increase computational time. Unreported results from this alternative approach indicate that, consistent with the visual inspection above, none of the interaction terms are statistically significant, with one notable exception. The interaction between cyclone exposure and the older age group is negative and statistically significant at the 5% level. This finding suggests that, consistent with the results from the separate regression approach, the impact of cyclones is statistically significantly greater for younger individuals.

7. Discussion of results and potential mechanisms

The findings from Section 4 underscore the significant impact of both current and lagged cyclones, particularly those of the greatest severity, on the likelihood of individuals acquiring PPHC. Notably, exposure to a category 5 cyclone within a 40 km radius of its eye is associated with the most substantial cumulative impact, amounting to 5.64 percentage points. This impact, representing approximately 11% of the mean prevalence of PPHC ownership (51%) in our sample, underscores the significance of cyclone events in influencing health insurance uptake.

Furthermore, this identified impact aligns with, and in some cases exceeds, 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 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 policy, which imposes penalties on those acquiring PPHC after turning 30, leading to a 1 to 4 percentage point increase in uptake.

We proceed to investigate the implications of PHI adoption for individuals. Although a rigorous causal analysis of the effects of PPHC on healthcare utilization is beyond the purview of this study due to data and identification limitations,[28] we present suggestive evidence that

[28] Identifying the causal impact of health insurance on health care utilization is methodologically demanding, as it requires the use of an appropriate strategy to address the potential endogeneity of health insurance enrolment. Endogeneity arises from unobservable individual factors, such as risk preferences and health risks, which may simultaneously affect both the demand for health insurance and the use of health care services (Cutler & Zeckhauser 2000). This challenge is further compounded by the limitations of the HILDA dataset, which does not consistently collect comprehensive measures of health care utilization (e.g., such measures are available only in Waves 9, 13, 17, and 21). To mitigate the potential endogeneity of PHI enrolment, this study employs an individual FE regression model, which controls for time-invariant unobservable factors. Furthermore, to address the issue of reverse causality, we use a one-year lag of PHI enrolment status to predict current health care utilization, allowing the estimates to be interpreted as the effects of prior PHI coverage on subsequent health care use. Unfortunately, the HILDA dataset lacks detailed health expenditure data at the individual level, limiting our ability to further explore the implications of health-related expenditures. Additionally, as previously discussed, the potential endogeneity of PHI enrolment presents challenges for making causal inferences about the relationship between PHI and health expenditure.

PPHC enrolment is associated with increased subsequent health care utilization. Specifically, Table 5 shows that, compared to individuals without PPHC, those with PPHC are statistically significantly ($p < 0.05$) more likely to have: (i) had any inpatient treatment in the last 12 months, by 2.18 pp; (ii) received any inpatient treatment as a private patient, by 4.57 pp; and (iii) visited a dentist, by 5.76 pp in the following year. This positive association between PPHC coverage and subsequent healthcare utilization—particularly for services such as inpatient private treatment and dental visits, which are typically not covered by the public health system—suggests the potential benefits of obtaining PPHC coverage. This finding is broadly consistent with prior research in the Australian context (for a recent review, see Nguyen *et al.* (2024)).

The remainder of this section delves into the role of various plausible factors contributing to the observed effects of cyclone exposure. To this end, we estimate an individual FE model, analogous to Equation (1), incorporating variables potentially influenced by cyclone exposure and associated with the demand for PHI as separate dependent variables. The estimated coefficients of the cyclone exposure variables from this adjusted equation offer insights into the potential mechanisms through which cyclone exposure may affect PPHC uptake. We exclusively concentrate on category 5 cyclone exposure, as our earlier findings indicate that other cyclone categories do not significantly impact PHI demand. Furthermore, we incorporate both contemporaneous and lagged values of cyclone exposure as explanatory variables in this revised model.

Both theoretical frameworks and empirical evidence underscore a variety of factors that affect the demand for health insurance (Cameron & Trivedi 1991; Cutler & Zeckhauser 2000; Barnes *et al.* 2023). These factors include income, health risks, premiums, and risk preferences. The comprehensive and detailed information contained in the HILDA dataset enhances its value for this analysis, as it enables the simultaneous exploration of multiple potential channels.

To examine the potential income channel, we incorporate several measures, including the individual's labour market income, irregular income, and normalized household total disposable income. Additionally, we examine the role of transfers from both private and public sources by including irregular transfers from non-resident parents or other non-household members, as well as income and non-income support payments from the Australian government.[29] It is important to note that our data may not capture all sources of transfers, particularly those related to disaster recovery funding programs. Furthermore, we assess potential health risk pathways by utilizing the individual's self-rated health along with the SF-36 general, physical, and mental health summary scores. Additionally, household annual expenditure on PHI is employed to investigate the potential premium channel. Finally, in line with previous Australian studies (Nguyen & Mitrou 2024c, a, d), we include variables related to weather-related home damage, home and content insurance, overall life satisfaction, and satisfaction concerning personal safety and health to capture potential psychological stress.[30] These variables are included due to their close association with risk preferences, which, similar to psychological stress, may have influenced the demand for PHI (Kahneman & Tversky 1979; Schildberg-Hörisch 2018).

[29] We aggregate irregular transfers from non-resident parents and other non-household members into a single category to enhance statistical power, as transfers from each individual source may not be substantial enough to warrant separate regressions. Similarly, income support payments from the Australian government encompass allowances, parenting payments, and pensions. Non-income support payments include benefits such as Family Tax Benefit Part A, Family Tax Benefit Part B, Maternity Payment, Mobility Allowance, Carer Allowance, Telephone Allowance, Maternity Immunisation Allowance, Seniors Concession Allowance, Double Orphan Pension, and Australian Government bonus payments. Unless otherwise specified, all income and transfer outcomes are measured over the last financial year (FY) and are adjusted for inflation using 2010 prices as the base year.

[30] "Home damage" is derived 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". "Overall life satisfaction" is derived from responses to the question, "All things considered, how satisfied are you with your life?" Respondents select a point on a scale from 0 ("Completely dissatisfied") to 10 ("Completely satisfied"), with higher scores indicating greater life satisfaction. Satisfaction with personal safety and health is based on respondents' evaluations of their perceived safety and health. The home damage variable is available beginning in Wave 9, whereas the life satisfaction variables are available in all survey waves.

The results from this analysis, presented in Table 6 (Panel A and Columns 1 and 2 – Panel B), suggest that income, transfers and health play a limited role in explaining our findings. In line with the Australian study by Nguyen and Mitrou (2024b), exposure to a category 5 cyclone does not have a statistically significant impact on income, transfers or health.[31] This finding is consistent with the results outlined in Section 5.3, which show that our main conclusions remain robust even when various income and health indicators are directly included in the analysis. Similarly, health insurance premiums do not appear to be a mechanism through which cyclones affect PPHC uptake, for two primary reasons. First, the regression results (Panel B – Column 3) indicate no statistically significant effect of cyclone exposure on premium payments among individuals who are already insured.[32] Second, the results in Section 5.3 demonstrate that our key findings remain robust even after directly including LGA premiums in the model.

[31] Our finding of no significant effect of cyclone exposure on income aligns with the evidence reported by Johar *et al.* (2022), which found no statistically significant association between natural disaster exposure, measured through home damage, and Australians' earnings. However, our finding contrasts with the mixed international evidence. For example, studies from the US report that individuals affected by hurricanes experience short-term reductions in earnings (one year after exposure) but observe earnings gains in the medium and long term (Deryugina *et al.* 2018; Groen *et al.* 2020). Deryugina (2017) also finds that US hurricanes lead to substantial increases in non-disaster-related government transfers in affected counties over the decade following a hurricane. In contrast, studies from the Philippines report a substantial reduction in income for cyclone-affected individuals (Anttila-Hughes & Hsiang 2013; Franklin & Labonne 2019).
Additionally, our finding of no significant impact of cyclone exposure on transfers contrasts with the evidence from the US presented in Barnes *et al.* (2023). Specifically, Barnes *et al.* (2023) report a positive relationship between disaster aid (measured at the parish level) and health insurance take-up rates, which they interpret as supporting the hypothesis that a significant portion of the effect is driven by post-disaster economic recovery. As noted above, differences in findings between Australian and US studies may be attributed to variations in study context, data and empirical models. It is important to emphasize that our finding of no significant impact of cyclone exposure on transfers should be interpreted with caution. As mentioned earlier, our data may not fully capture transfers from disaster recovery funding programs (Kucuk & Ulubasoglu 2024).
[32] In this regression, we use household annual expenditure on PHI, as detailed in Section 5.3, as the dependent variable. The analysis is restricted to individuals with positive household PHI expenditure (approximately 60% of those with valid data) to distinguish the effect of cyclones on PHI enrolment from that on premiums. Consequently, these results are not directly comparable to the main findings, which use PPHC coverage as the outcome variable, derived from a different question. The lack of a statistically significant effect of cyclone exposure on PHI premiums aligns with the Australian policy context. While PHI providers in Australia can adjust premiums based on regional factors, these regions are typically broad, such as state/territory or rural/urban areas, and remain stable over time (Duckett & Nemet 2019). Thus, it is unlikely that cyclones would significantly influence premiums in affected regions, which are defined at a finer geographical scale (postcode) and vary over time in our framework. Additionally, our model accounts for regional and temporal variations in PHI premiums by controlling for region fixed effects and time fixed effects. Our finding of no significant effect of cyclones on PHI premiums is different from the empirical evidence from prior research demonstrating that natural disasters can escalate residential insurance premiums (Born & Viscusi 2006; Kousky 2019; Kraehnert et al. 2021).

The coefficient for concurrent cyclone exposure on weather-related home damage, presented in Panel B - Column 4, demonstrates a positive and statistically significant effect at the 5% level. This finding indicates that individuals directly affected by cyclones are more likely to report instances of home damage.[33] This result aligns with a similar discovery by Nguyen and Mitrou (2024d). When considered in conjunction with the observed diminishing impact of weather-related home damage on individuals' perceived control over their life outcomes (Nguyen & Mitrou 2024c) or life satisfaction (Nguyen & Mitrou 2024a), it suggests that such damage may serve as a mediating factor through which cyclone exposure increases PPHC enrolment in the current study.

The statistically significant negative estimates of cyclone exposure on overall life satisfaction and the two satisfaction domains related to personal safety and health (Panel B, Columns 6-8) suggest that psychological stress may be a potential mechanism. Specifically, consistent with the findings of Nguyen and Mitrou (2024a), cyclone exposure exerts a statistically significant (at the 5% level) negative concurrent effect on overall life satisfaction and health satisfaction, as well as a delayed impact on personal safety satisfaction. These significant negative effects on psychological outcomes— closely linked to risk preferences, which have been hypothesized to influence health insurance demand (Kahneman & Tversky 1979; Kimball 1993; Cutler & Zeckhauser 2000; Schildberg-Hörisch 2018) — suggest that psychological stress may be a contributing factor in the observed increase in PHI enrolment following cyclone exposure.

Overall, these findings indicate that while income, transfers, health status, and premiums are unlikely pathways for the observed increase in PHI uptake, cyclone-induced home damage and

[33] Interestingly, the coefficient for lagged cyclone exposure on home damage exhibits a negative and statistically significant effect at the 1% level. This outcome is consistent with findings from an Australian study conducted by Nguyen and Mitrou (2024d). The authors attribute the lower reported home damage among individuals who have experienced a cyclone in the preceding year to their proactive purchase of residential insurance in response to the initial event. Our results, presented in Panel B – Column 5, also reveal that exposure to a category 5 cyclone is associated with a statistically significant increase in the likelihood of having home and content insurance in the same year. This acquired protection contributes to mitigating the impact of future cyclones, resulting in reduced reported damage.

heightened psychological stress—manifesting in a diminished sense of control over life outcomes and reduced satisfaction with health and personal safety—are plausible channels through which cyclone exposure influences PHI enrolment.

Our finding of a positive association between cyclones and PHI acquisition implies that individuals affected by the most severe category 5 cyclones 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 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).[34]

Our recognition of the positive impact of cyclones on PHI enrolment, when juxtaposed with the existing evidence highlighting the role of PHI in enhancing healthcare utilization in Australia (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 may serve as a coping mechanism. This mechanism allows individuals to protect themselves against future health-related costs. Analogous to how residential insurance helps alleviate future residential damage caused by subsequent cyclones, as demonstrated in Nguyen and Mitrou (2024d), the acquisition of PHI may assist individuals in addressing forthcoming healthcare needs.

[34] 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.

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 statistically significant increase in PHI acquisition following cyclones in both the current and preceding years. This effect is particularly pronounced for category 5 cyclones, the most severe, and is only statistically significant for these cyclones, especially those occurring in closer proximity to individuals' homes. For instance, the most substantial cumulative impact, reaching 5.64 percentage points, is observed with exposure to a category 5 cyclone within a 40 km radius of its eye. This newly identified effect of cyclone exposure on PHI uptake mirrors, and in some cases surpasses, the influence of certain policies designed to bolster enrolment rates in Australia. Furthermore, our findings withstand a series of sensitivity assessments, including three randomization tests.

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, younger individuals, healthier individuals, renters, affluent individuals, those with prior residential insurance coverage, and residents of coastal 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 socio-economically advantaged backgrounds, particularly indicated higher income, underscores the necessity for tailored support policies targeting vulnerable populations to utilize this natural disaster coping mechanism.

We also find that PHI uptake leads to an increase in subsequent healthcare utilization, particularly for services not covered by the public health system. Moreover, after ruling out income, transfers, health status, and premiums as potential mechanisms, our study offers suggestive evidence that cyclone-induced home damage and elevated psychological stress are plausible pathways through which cyclone exposure increases PHI enrolment.

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 PHI 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 PHI enrolment. A more nuanced understanding of the relationship between natural disasters, risk preferences, and insurance is particularly crucial, given the pervasive underinsurance in both health and residential insurance markets, despite various incentives (Gallagher 2014; Wagner 2022). Such insights could inform the development of policies aimed at enhancing insurance uptake. Secondly, exploring the subsequent causal implications of cyclone-induced health insurance acquisition on healthcare expenditure 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 status

	Affected by any cyclone	Unaffected	Affected - Unaffected (1) - (2)
	(1)	(2)	(3)
Age (years)	44.790	45.745	-0.956***
Married/De facto [(a)]	0.630	0.632	-0.002
Separated/divorced/widowed [(a)]	0.136	0.137	-0.001
Year 12 [(a)]	0.156	0.153	0.003
Vocational or training qualification [(a)]	0.407	0.380	0.027***
Bachelor or higher [(a)]	0.175	0.205	-0.030***
Household size	2.842	2.872	-0.030*
Major city [(a)]	0.408	0.616	-0.207***
Local area unemployment rate (%)	5.033	5.269	-0.236***
Local area SEIFA index	5.051	5.442	-0.391***
Have PPHC [(a)]	0.493	0.505	-0.012**
Observations	7,221	107,000	

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

	(1)	(2)	(3)	(4)	(5)	(6)
Current category 1	-0.78	-0.90	-0.66	-0.78		
	[0.68]	[0.71]	[0.75]	[0.77]		
Current category 2	-0.23	-0.44	0.30	3.11		
	[1.28]	[1.40]	[1.33]	[2.65]		
Current category 3	0.14	-0.09	0.28	0.98		
	[1.45]	[1.30]	[1.33]	[1.33]		
Current category 4	0.85	0.88	0.72	0.61		
	[0.55]	[0.58]	[0.60]	[0.59]		
Current category 5	2.82***	2.47***	2.67***	3.16***	2.64***	5.29***
	[0.78]	[0.88]	[0.93]	[0.90]	[0.84]	[1.41]
One-year lagged category 1		-0.12	-0.67	-0.94		
		[0.75]	[0.79]	[1.11]		
One-year lagged category 2		1.08	1.58	2.37		
		[1.38]	[1.69]	[1.89]		
One-year lagged category 3		-0.52	-0.35	0.79		
		[0.98]	[1.31]	[1.02]		
One-year lagged category 4		0.07	-0.24	-0.17		
		[0.58]	[0.62]	[0.62]		
One-year lagged category 5		2.54***	2.77***	2.93***	2.65***	
		[0.94]	[1.02]	[0.96]	[0.93]	
Two-year lagged category 1			-0.46			
			[0.89]			
Two-year lagged category 2			-1.16			
			[1.58]			
Two-year lagged category 3			0.76			
			[1.48]			
Two-year lagged category 4			-1.57***			
			[0.59]			
Two-year lagged category 5			0.05			
			[1.02]			
One-year lead category 1				0.08		
				[0.68]		
One-year lead category 2				0.43		
				[1.01]		
One-year lead category 3				1.58		
				[1.13]		
One-year lead category 4				1.86***		
				[0.60]		
One-year lead category 5				1.15		
				[1.00]		
Observations	113,785	106,694	99,079	91,753	106,694	106,694
Number of unique individuals	16,069	14,527	13,383	13,068	14,527	14,527

Notes: Results reported in each column are from a separate linear individual FE regression, using Equation (1). Results in Column 6 are estimated from the transformed Equation (2). The reference group consists of individuals who were not affected by any cyclone within 100 km of its eye in the respective year. Results (coefficient estimates and standard errors) 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, postcode dummies, survey year dummies, and survey month dummies. Robust standard errors clustered at the postcode 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)	(10)	(11)
Panel A:	Baseline	Sample: Whole Australia	Sample: Stayers	Sample: Movers	Excluding postcode dummies	Clustering at the individual level	Employing a pooled OLS regression model	Applying a Random Effects linear model	Excluding select time-variant variables	Using one-year lag of select time-variant variables	Including LGA PHI premium
Concurrent cyclone	2.64***	2.40***	2.00**	5.53*	2.74***	2.64***	3.38***	2.86***	2.42***	2.30***	2.61***
	[0.84]	[0.85]	[0.89]	[2.95]	[0.83]	[0.96]	[1.22]	[0.83]	[0.85]	[0.85]	[0.86]
Lagged cyclone	2.65***	2.51***	2.07***	4.53	2.74***	2.65***	3.10***	2.65***	2.46***	2.79***	2.70***
	[0.93]	[0.92]	[0.78]	[3.42]	[0.94]	[0.88]	[1.14]	[0.95]	[0.94]	[0.94]	[0.97]
Observations	106,694	176,777	89,383	17,311	106,694	106,694	106,694	106,694	106,694	106,694	105,117
Num of unique individuals	14,527	23,152	13,987	7,874	14,527	14,527		14,527	14,527	14,527	14,447
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	Including satisfaction about health	Including week of year dummies	Applying a Random Effects logit model
Concurrent cyclone	2.62***	2.66***	2.64***	2.42***	2.69***	2.56***	2.54***	2.56***	2.63***	2.63***	3.06***
	[0.85]	[0.84]	[0.84]	[0.82]	[0.85]	[0.83]	[0.83]	[0.83]	[0.84]	[0.84]	[0.94]
Lagged cyclone	2.65***	2.66***	2.67***	3.06***	2.60***	3.08***	3.06***	3.04***	2.65***	2.64***	2.79***
	[0.94]	[0.94]	[0.94]	[1.01]	[0.93]	[1.04]	[1.01]	[1.03]	[0.94]	[0.94]	[0.88]
Observations	106,694	106,548	106,694	96,669	106,543	96,536	96,506	97,068	106,641	106,694	106,694
Num of unique individuals	14,527	14,521	14,527	13,962	14,524	13,938	13,953	13,954	14,524	14,527	

Notes: The results presented in each column and panel are from a separate linear FE regression, using Equation (1), unless otherwise specified. Cyclone exposure measure: Category 5 cyclone within 100km from its eye. Results (coefficient estimates and standard errors) 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, postcode dummies, year dummies, and survey month dummies. Robust standard errors clustered at the postcode 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: Cumulative impacts of cyclones by distances to the cyclone's eye

Distance to cyclone eye:	≤40km	>40km and ≤100km	>100km and ≤200km
	(1)	(2)	(3)
Exposure to a category 5 cyclone	5.64***	4.77***	3.10**
	[2.13]	[1.63]	[1.38]
Observations	106,723	106,723	106,723
Number of unique individuals	14,527	14,527	14,527
Mean of dependent variable	51.19	51.19	51.19
Proportion affected (%)	0.39	0.38	0.71

Notes: Results reported in each column are from a separate linear FE regression, using the transformed Equation (2). The estimated effect represents the cumulative impact of both current and lagged cyclone exposure on current PPHC enrolment. 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, postcode dummies, year dummies, and survey month dummies. Robust standard errors clustered at the postcode level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: Effects of private health insurance coverage on subsequent health care utilization

	Any health check-ups or tests in the last 12 months	Any family or GP visit in the last 12 months	Any inpatient treatment in the last 12 months	Any inpatient treatment as private patient in the last 12 months	Any dentist visit in the last 12 months
	(1)	(2)	(3)	(4)	(5)
One-year lagged PPHC	0.77	0.05	2.18***	4.57***	5.76***
	[0.95]	[0.80]	[0.76]	[0.52]	[1.07]
Observations	48,056	48,050	48,062	48,045	48,015
Number of unique individuals	20,823	20,818	20,822	20,819	20,813
Mean of dependent variable	72.90	84.78	13.32	5.86	55.53

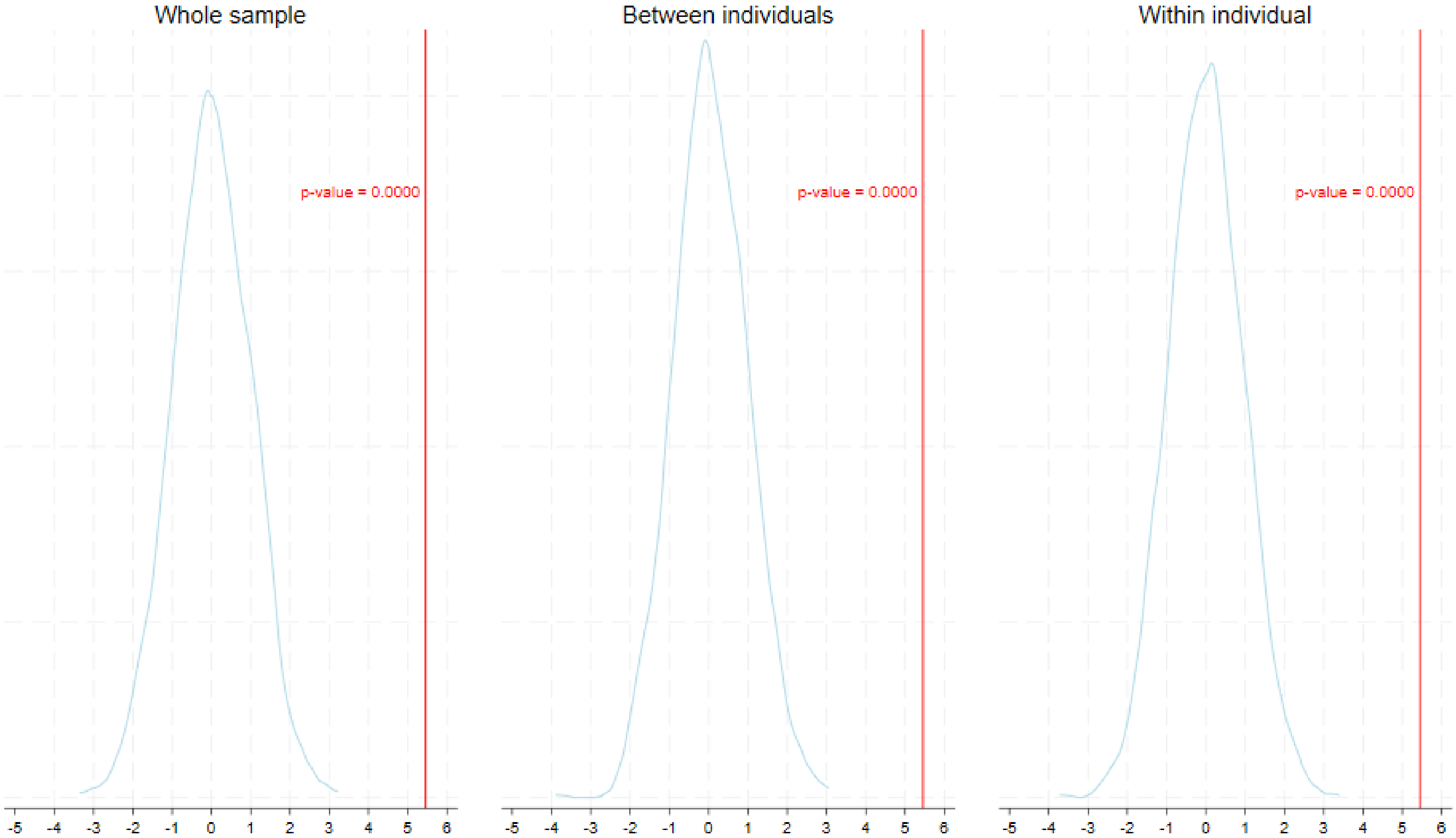
Notes: The results presented in each column are based on a separate linear FE regression of current health care use on one-year lagged PPHC. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Other explanatory variables include age (and its 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.

Table 6: Additional results and potential mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Individual's annual labour market income (FY, $1,000, 2010 price)	Individual's irregular income (FY, $1,000, 2010 price)	Equivalised household disposable income (FY, $1,000, 2010 price)	Irregular transfers from non-resident parents and other non-household members (FY, $1,000, 2010 price)	Australian Government income support payments (FY, $1,000, 2010 price)	Australian Government non-income support payments (FY, $1,000, 2010 price)	Self-rated health (1-5 scale, higher is healthier)	SF36 general health summary (0-100 scale, higher is healthier)
Concurrent cyclone	0.38	-0.52	-0.14	-0.03	-0.19*	-0.04	-0.01	-0.20
	[0.90]	[0.43]	[1.00]	[0.07]	[0.12]	[0.06]	[0.02]	[0.36]
Lagged cyclone	-0.76	-0.60	-0.77	-0.08*	0.06	-0.01	0.03	0.07
	[0.78]	[0.61]	[1.10]	[0.04]	[0.11]	[0.09]	[0.02]	[0.43]
Observations	179,239	179,023	179,239	179,239	177,678	179,026	161,227	160,968
Num of unique individuals	18,063	18,060	18,063	18,063	18,034	18,061	17,341	17,316
Mean of dependent variable	41.35	2.21	52.31	0.18	3.44	1.32	3.34	67.25
Panel B:	SF36 physical health summary (0-100 scale, higher is healthier)	SF36 mental health summary (0-100 scale, higher is healthier)	Annual household expenditure on PHI ($1,000, 2010 price)	Weather related home damage (Binary variable)	Had home and content insurance (Binary variable)	Overall life satisfaction (1-10 scale, higher is more satisfied)	Personal safety satisfaction (1-10 scale, higher is more satisfied)	Health satisfaction (1-10 scale, higher is more satisfied)
Concurrent cyclone	-0.53	-0.30	-0.02	7.28**	4.95***	-0.10**	-0.11**	-0.04
	[0.55]	[0.36]	[0.05]	[3.36]	[1.89]	[0.04]	[0.05]	[0.05]
Lagged cyclone	0.82	-0.33	-0.06	-2.30***	2.64	0.02	-0.01	-0.10**
	[0.55]	[0.35]	[0.07]	[0.86]	[1.86]	[0.04]	[0.04]	[0.04]
Observations	161,052	162,197	82,215	116,843	131,587	179,141	179,152	179,074
Num of unique individuals	17,323	17,346	10,938	14,815	15,712	18,059	18,062	18,058
Mean of dependent variable	82.60	73.59	2.12	2.02	51.36	7.92	7.22	8.23

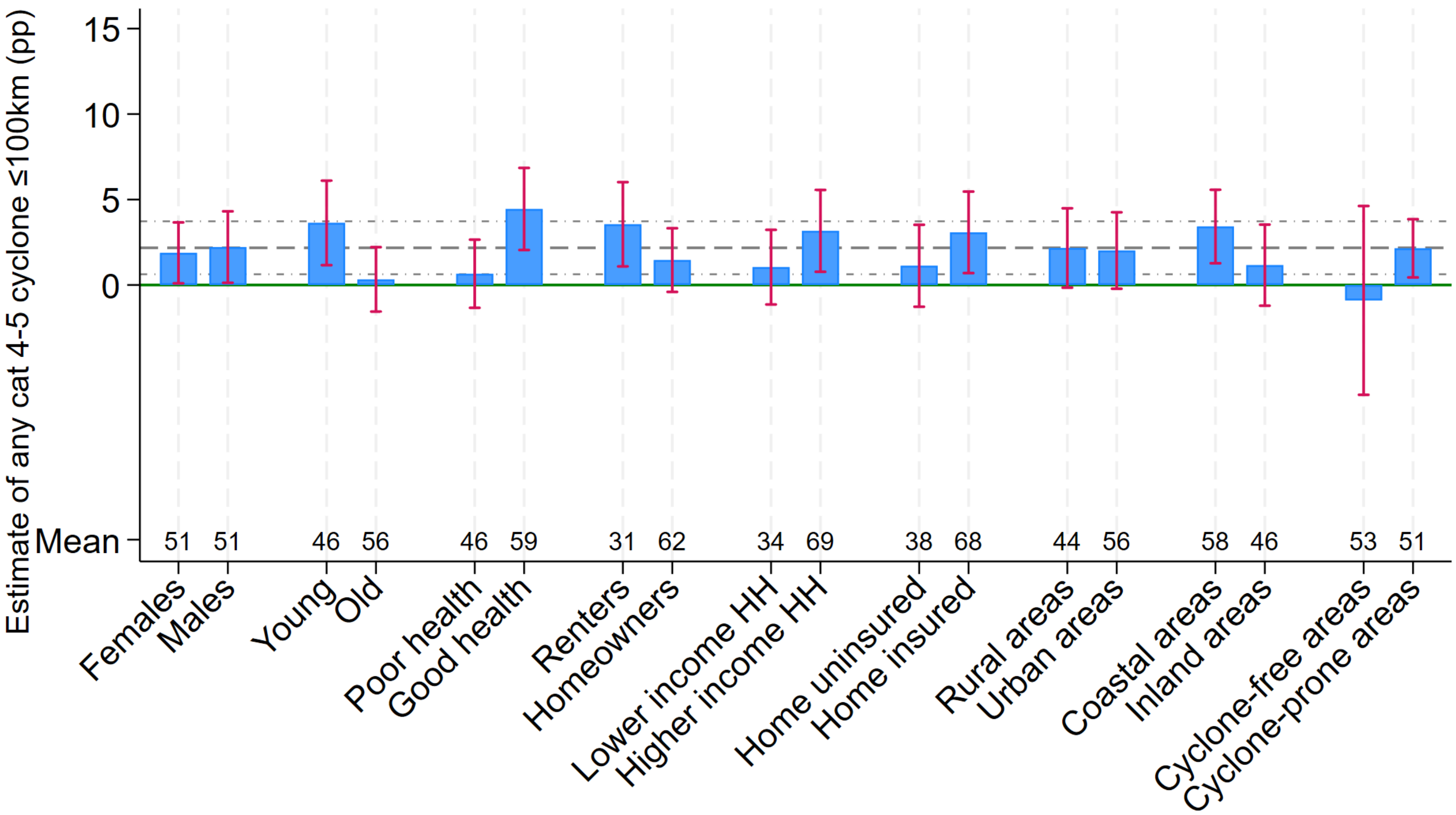
Notes: Results reported in each column and panel are from a separate linear FE regression. Cyclone exposure measure: Category 5 cyclone within 100km from its eye. Sample includes individuals residing in New South Wales, Queensland, Western Australia, and the Northern Territory. For binary outcome variables, 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, postcode dummies, year dummies, and survey month dummies. Robust standard errors clustered at the postcode level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 1: Randomization tests



Notes: This figure illustrates the distribution of 1,000 regression estimates of the cumulative effect of random assignment of exposure to a category 5 cyclone within 100 km of its eye. The vertical red line indicates the observed cumulative effect of exposure to a category 5 cyclone within 100 km of its eye, as obtained from real data. The transformed regression specified in Equation (2) is utilized in this experiment. The p-value is calculated as the probability that the estimate from the real data is greater than or equal to the estimates from the randomized data.

Figure 2: Heterogeneity in the cyclone impact on private patient hospital cover uptake



Notes: Results for each subgroup are obtained from a separate FE regression, using Equation (2). The estimated effect represents the cumulative impact of both current and lagged cyclone exposure on current PPHC enrolment. Dependent variable: private patient hospital cover. Cyclone exposure measure: Any category 4 to 5 cyclone within 100 km. 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 dependent variable for each subgroup printed below the bars. Detailed regression results are reported in Appendix Table A4.

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			Count of individuals affected
					Overall	Between	Within	
Age	The respondent's age at the survey time (years)	45.68	15.00	101.00	19.12	19.81	2.82	
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	0.21	
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	0.15	
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	0.46	0.13	
Bachelor or higher	Dummy: = 1 if the individual has a bachelor degree or higher and zero otherwise	0.20	0.00	1.00	0.40	0.38	0.11	
Household size	Number of household members	2.87	1.00	17.00	1.49	1.41	0.71	
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	0.16	
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	5.25	2.30	8.00	1.10	0.68	0.99	
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area	5.42	1.00	10.00	2.86	2.69	1.08	
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	0.21	
Maximum wind speed within 100 km	Maximum wind speed of any cyclone within 100km from the individual's residential postcode centroid in the last year (zero if unaffected)	8.638	0.00	250.20	36.22	18.24	33.30	
Any category 1 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 1 cyclone's eye last year and zero otherwise	0.021	0.00	1.00	0.14	0.09	0.13	2,363
Any category 2 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 2 cyclone's eye last year and zero otherwise	0.006	0.00	1.00	0.08	0.05	0.07	677
Any category 3 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 3 cyclone's eye last year and zero otherwise	0.004	0.00	1.00	0.07	0.04	0.06	494
Any category 4 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 4 cyclone's eye last year and zero otherwise	0.024	0.00	1.00	0.15	0.07	0.15	2,784
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	0.008	0.00	1.00	0.09	0.04	0.08	903

Notes: Sample of 113,785 observations.

Appendix Table A2: Determinants of attrition

Dependent variable:	Attrition due to any reason	Attrition due to death
	(1)	(2)
Current category 1	-1.13**	-0.17
	[0.53]	[0.16]
Current category 2	0.49	0.03
	[1.15]	[0.35]
Current category 3	-1.84**	-0.33
	[0.88]	[0.22]
Current category 4	0.21	0.03
	[0.49]	[0.17]
Current category 5	-1.12*	-0.19
	[0.63]	[0.19]
One-year lagged category 1	-0.79	-0.13
	[0.73]	[0.21]
One-year lagged category 2	-0.35	0.20
	[1.04]	[0.44]
One-year lagged category 3	1.14	-0.25
	[1.02]	[0.22]
One-year lagged category 4	-0.06	0.13
	[0.47]	[0.18]
One-year lagged category 5	-0.12	-0.31**
	[0.64]	[0.16]
Age	-3.39***	-0.26
	[1.25]	[0.26]
Age squared	0.01***	0.01***
	[0.00]	[0.00]
Married/De facto [(a)]	0.18	0.47***
	[0.35]	[0.05]
Separated/divorced/widowed [(a)]	0.12	0.89***
	[0.49]	[0.15]
Year 12 [(b)]	5.40***	0.58***
	[0.43]	[0.05]
Vocational or Training qualification [(b)]	4.69***	0.77***
	[0.48]	[0.09]
Bachelor or higher [(b)]	6.03***	1.23***
	[0.58]	[0.09]
Household size	0.03	0.08***
	[0.07]	[0.01]
Observations	170,179	170,179
Number of unique individuals	17,702	17,702
Mean of dependent variable (%)	6.25	0.59
R squared	0.02	0.02
P value (Wald test)	0.13	0.48

Notes: Results reported in each column are from a separate linear FE regression. Results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. [(a)] and [(b)] indicates "Single" and "Under Year 12" as the comparison group, respectively. "P value" reports the P-value from a Wald test for the null hypothesis that the coefficients of all cyclone exposure variables are equal to zero. Other explanatory variables include local area socio-economic variables, state/territory dummies, year dummies, and survey month dummies. Robust standard errors clustered at the postcode level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A3: Testing for non-linearity in wind speed effects

Functional form of wind speed variable:	Linear	Logarithmic	Quadratic	Cubic	Binary	50 km/h increments
	(1)	(2)	(3)	(4)	(5)	(6)
Current wind speed (km/h)	2.10***		-2.60	16.51		
	[0.67]		[3.40]	[18.93]		
One-year lagged wind speed (km/h)	1.03		-5.87*	-1.45		
	[0.66]		[3.50]	[24.39]		
Logarithm of current wind speed		2.36***				
		[0.81]				
Logarithm of one-year lagged wind speed		0.99				
		[0.80]				
Current wind speed squared			0.02	-0.12		
			[0.01]	[0.13]		
Lagged wind speed squared			0.03**	-0.01		
			[0.01]	[0.17]		
Current wind speed cubed				0.00		
				[0.00]		
Lagged wind speed cubed				0.00		
				[0.00]		
Current any cyclone exposure					0.28	
					[0.38]	
Lagged any cyclone exposure					0.41	
					[0.41]	
Current wind speed ≥ 50 and < 100 km						-0.89
						[0.71]
Current wind speed ≥ 100 and < 150 km						-0.04
						[0.94]
Current wind speed ≥ 150 and < 200 km						0.77
						[0.58]
Current wind speed ≥ 200 km						2.63***
						[0.84]
Lagged wind speed ≥ 50 and < 100 km						-0.12
						[0.74]
Lagged wind speed ≥ 100 and < 150 km						-0.32
						[1.01]
Lagged wind speed ≥ 150 and < 200 km						0.08
						[0.58]
Lagged wind speed ≥ 200 km						2.57***
						[0.94]

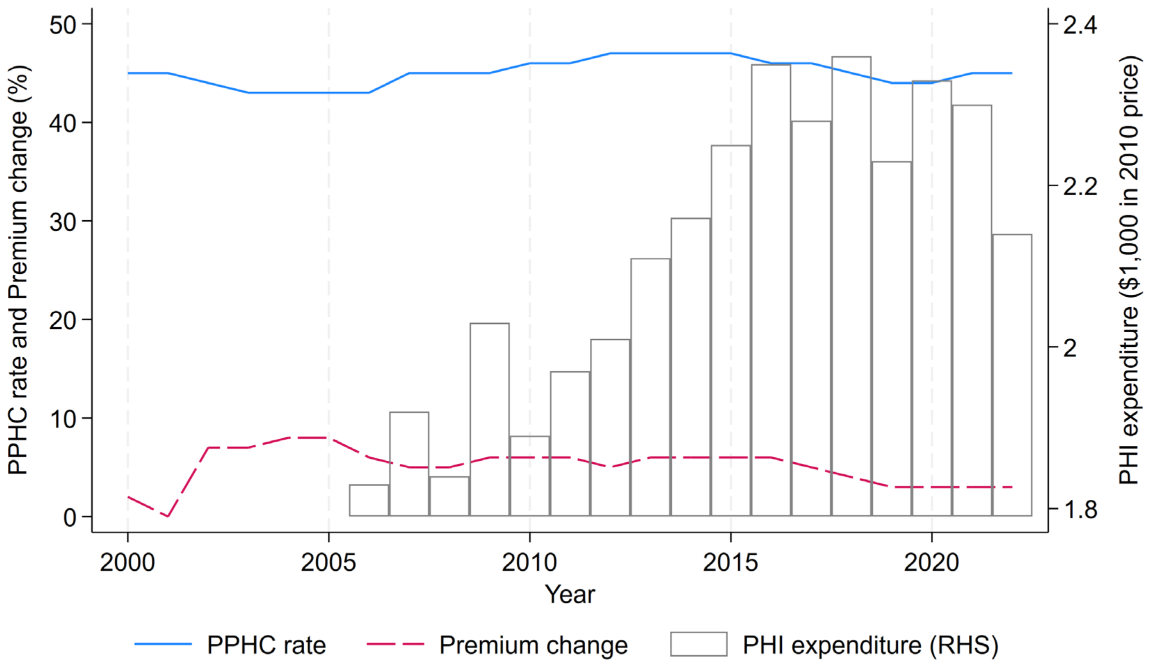
Notes: Results reported in each column are from a separate FE regression. Results (coefficient estimates and standard errors) are multiplied by 100 in Columns 2, 5, and 6 and by 10,000 in remaining columns for aesthetic purposes. Sample size: 106,694 observations (14,527 unique persons). Other explanatory variables include age (and its square), marital status, education, household size, local area socio-economic variables, postcode dummies, year dummies, and survey month dummies. The regressions reported in Columns 1 to 4 also control for both current and lagged dummy variables indicating whether an individual was unaffected by a cyclone. Robust standard errors clustered at the postcode level in squared brackets. 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 private patient hospital cover uptake – Separate regressions for each subgroup

	(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 4 to 5 cyclone within 100 km (cumulative effect)	1.88**	2.22**	3.63***	0.33	0.66	4.45***	3.55***	1.46	1.04	3.17***
	[0.91]	[1.07]	[1.26]	[0.96]	[1.02]	[1.22]	[1.26]	[0.95]	[1.11]	[1.22]
Observations	56,348	50,375	53,668	51,536	49,682	45,393	35,244	67,431	51,139	51,536
Number of unique individuals	7,526	7,001	8,040	6,511	6,373	5,970	4,534	7,809	6,148	6,195
Mean of dep. variable	51.38	50.98	46.42	56.41	46.10	59.22	31.23	62.27	33.76	69.33
Proportion affected (%)	3.22	3.23	3.38	3.12	3.47	3.10	3.65	3.07	3.41	3.12
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 4 to 5 cyclone within 100 km (cumulative effect)	1.12	3.08**	2.16*	2.02*	3.42***	1.16	-0.90	2.15**		
	[1.22]	[1.21]	[1.18]	[1.14]	[1.10]	[1.21]	[2.81]	[0.87]		
Observations	45,211	46,513	39,503	62,298	50,555	51,246	53,776	48,025		
Number of unique individuals	6,352	5,839	4,727	7,464	6,104	6,087	6,467	5,724		
Mean of dep. variable	37.56	67.78	44.26	56.46	57.53	46.00	52.64	50.70		
Proportion affected (%)	3.51	3.07	3.88	2.87	3.49	3.05	0.46	6.41		

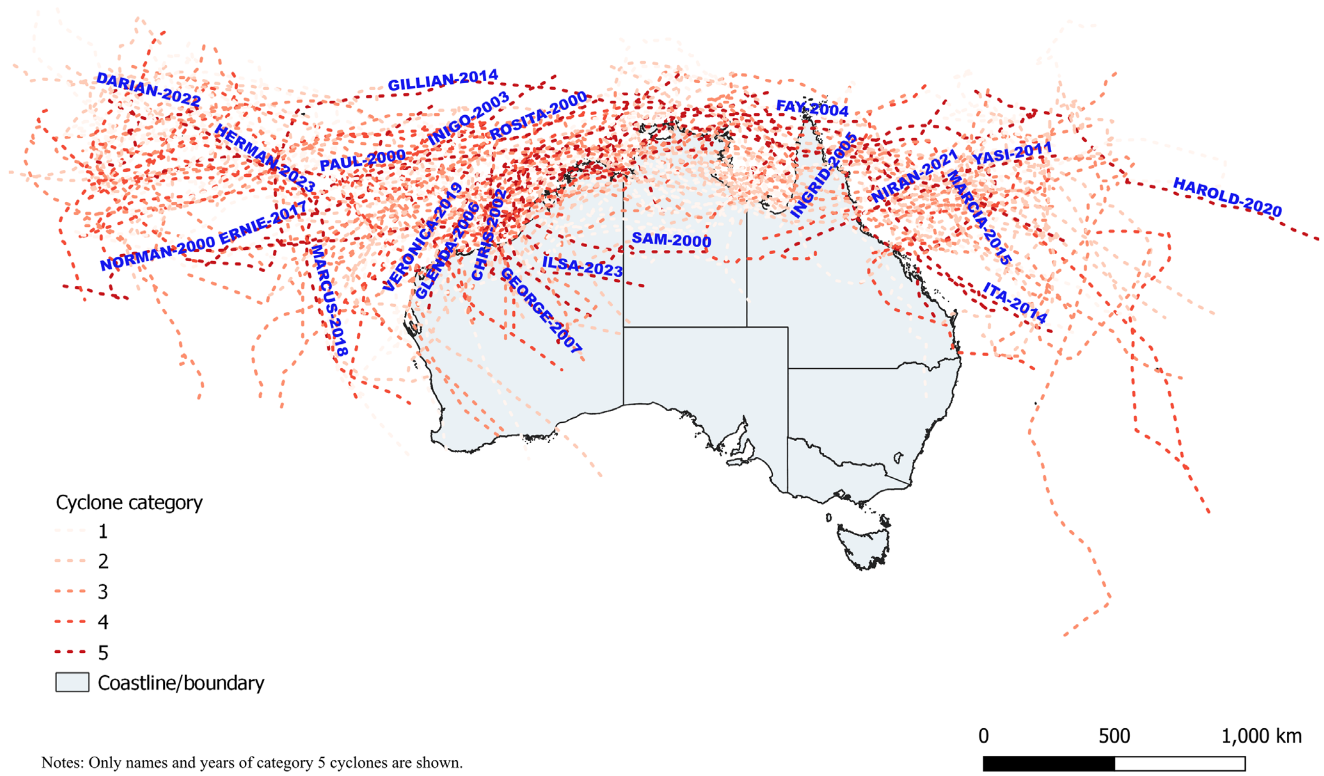
Notes: The results presented in each column and panel are based on a separate linear FE regression, using the transformed Equation (2). The estimated effect represents the cumulative impact of both current and lagged cyclone exposure on current PPHC enrolment. Results (coefficient estimates, standard 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, postcode dummies, year dummies, and survey month dummies. Robust standard errors clustered at the postcode level in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Figure A1: Private health insurance coverage, premium and expenditure over time



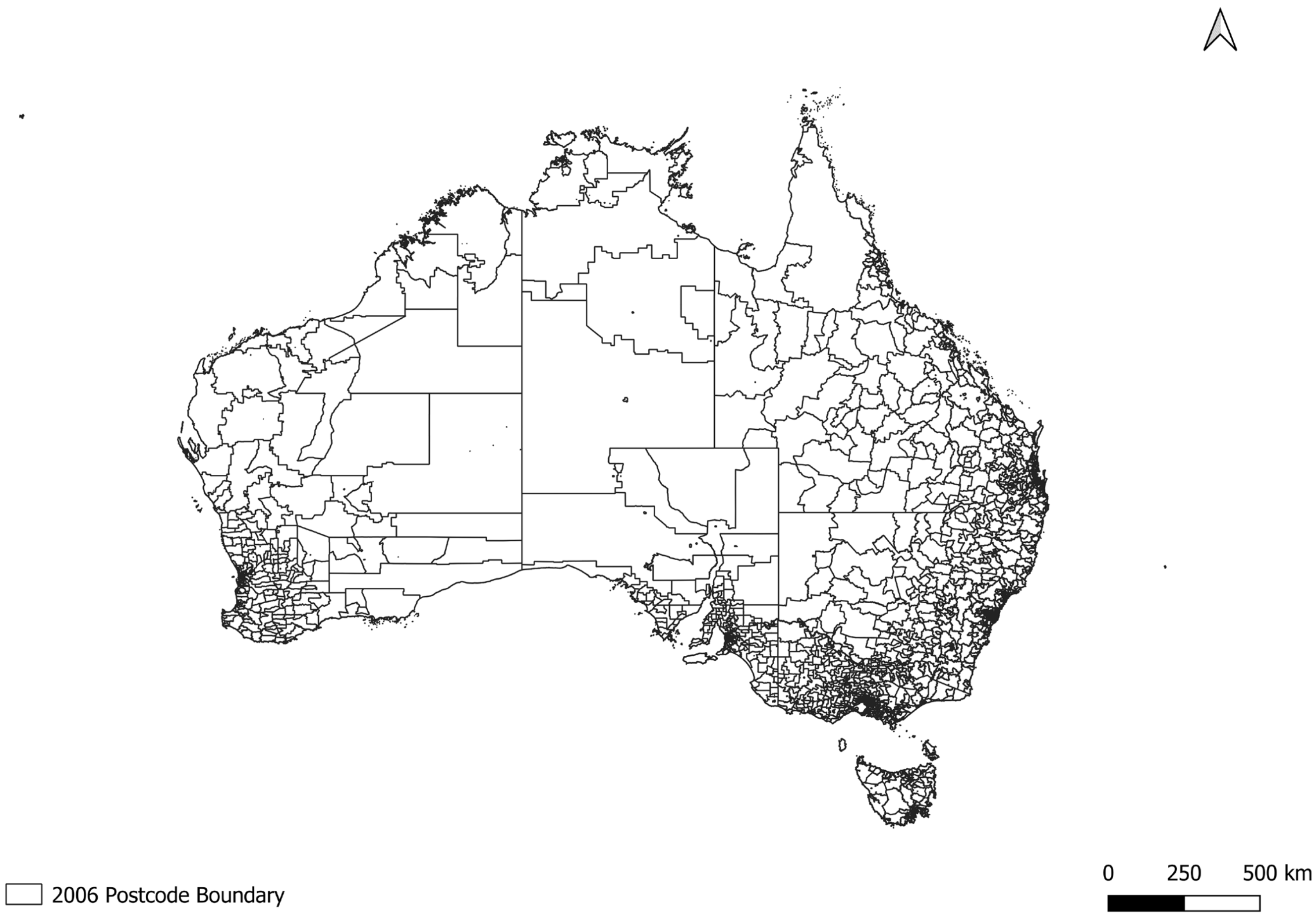
Notes: Annual PPHC rate data, expressed as a percentage, are obtained from the Australian Prudential Regulation Authority and recorded as of December each year. Data on annual changes in premiums, measured as a percentage, are obtained from the Department of Health and Aged Care and reflect the average annual change across all PHI providers. Annual PHI expenditure is calculated by taking the annual average of all positive PHI expenditures reported by individuals surveyed in the HILDA survey, measured in AU$1,000 and adjusted for inflation using 2010 consumer price index as the base.

Appendix Figure A2: Tropical cyclone hit map between 2000 and 2023



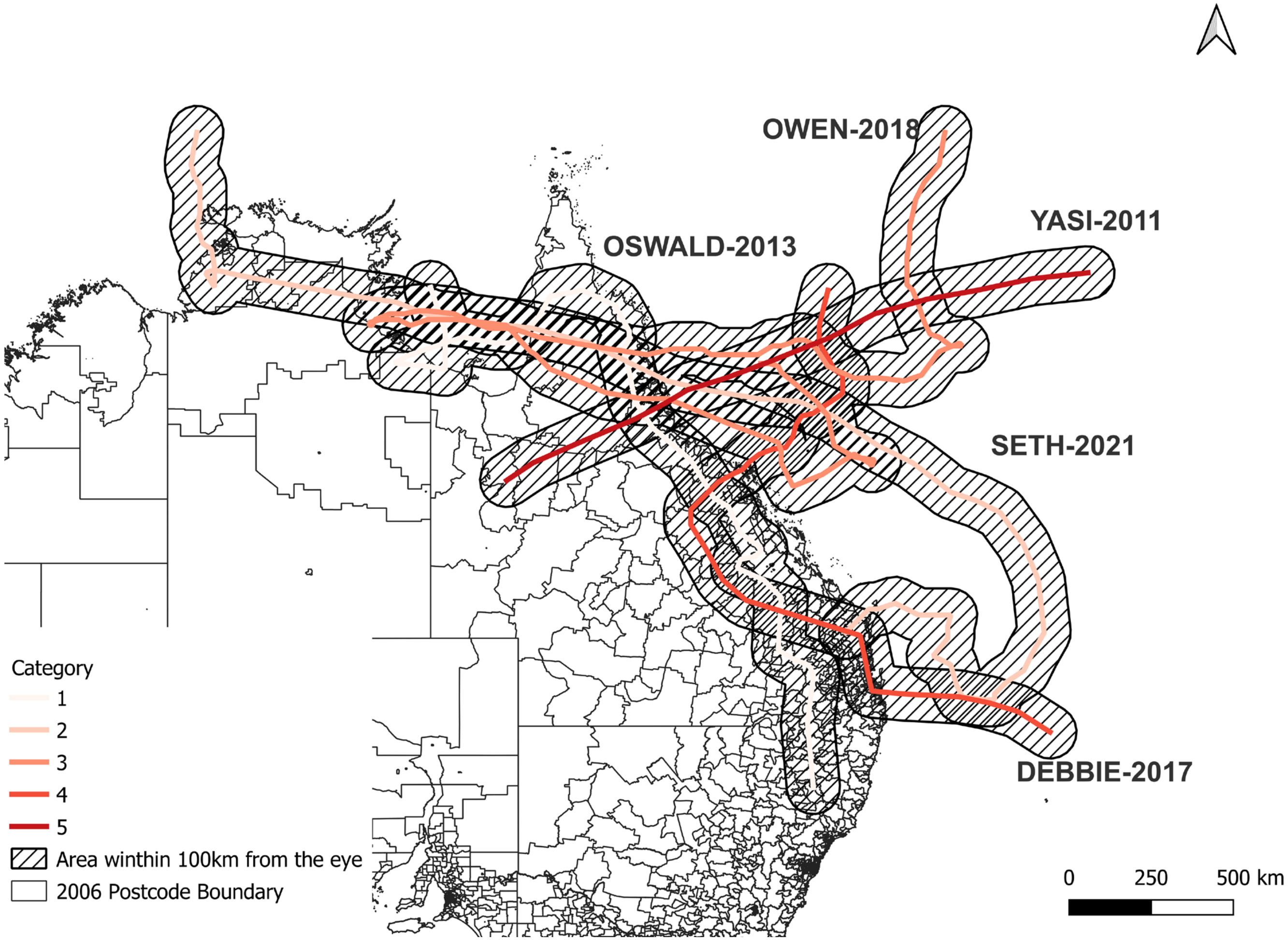
Notes: Cyclone category is classified using the maximum mean wind speed cut-offs from BOM. Cyclones are available up to November 2023.

Appendix Figure A3: 2006 postal code boundaries in Australia



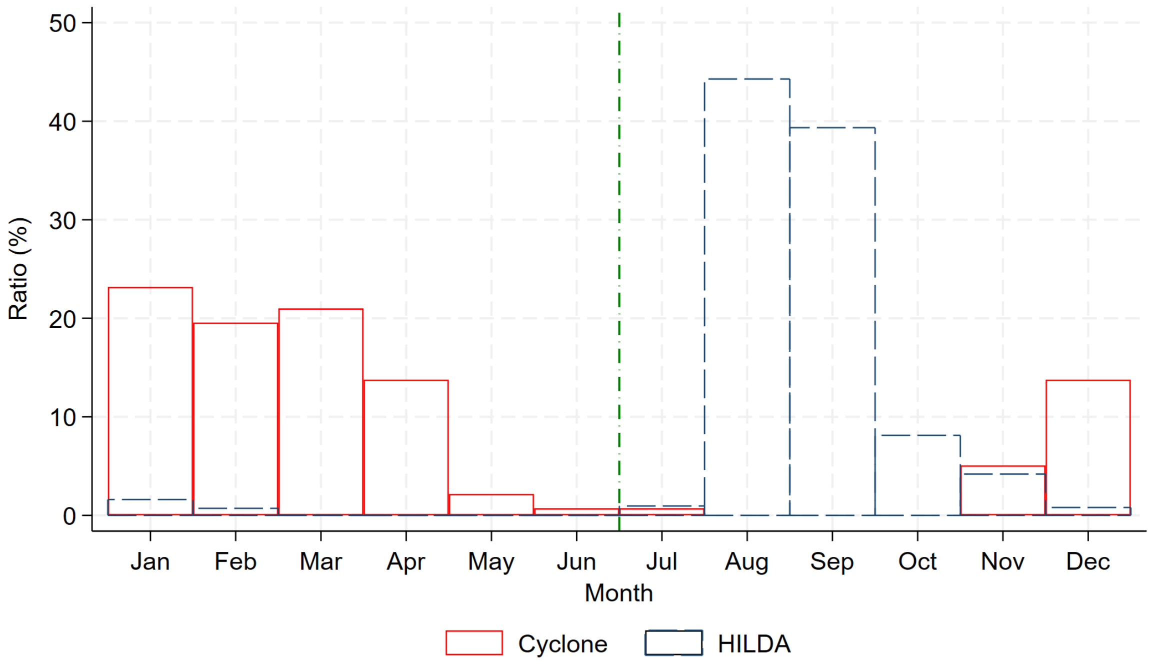
Notes: Postal Areas 2006 shapefile is obtained from the Australian Bureau of Statistics.

Appendix Figure A4: An example of postcodes affected by selected cyclones



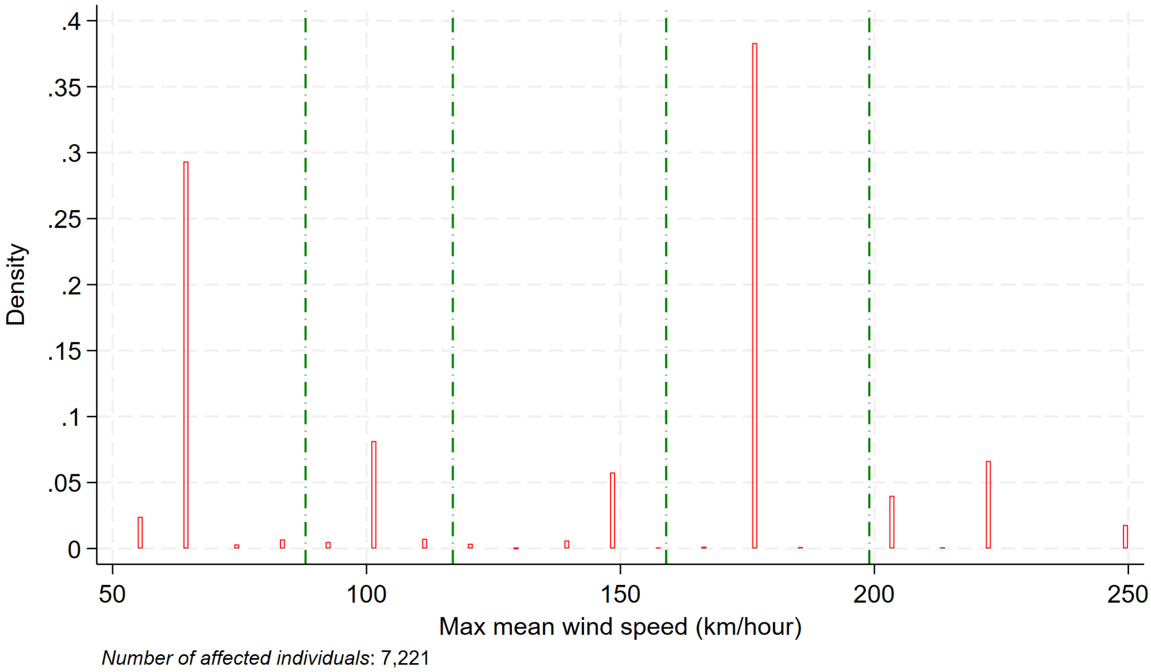
Notes: The Postal Areas 2006 shapefile was obtained from the Australian Bureau of Statistics. Cyclone names and their respective years are displayed next to each cyclone.

Appendix Figure A5: Distribution of cyclone occurrence and HILDA interview dates



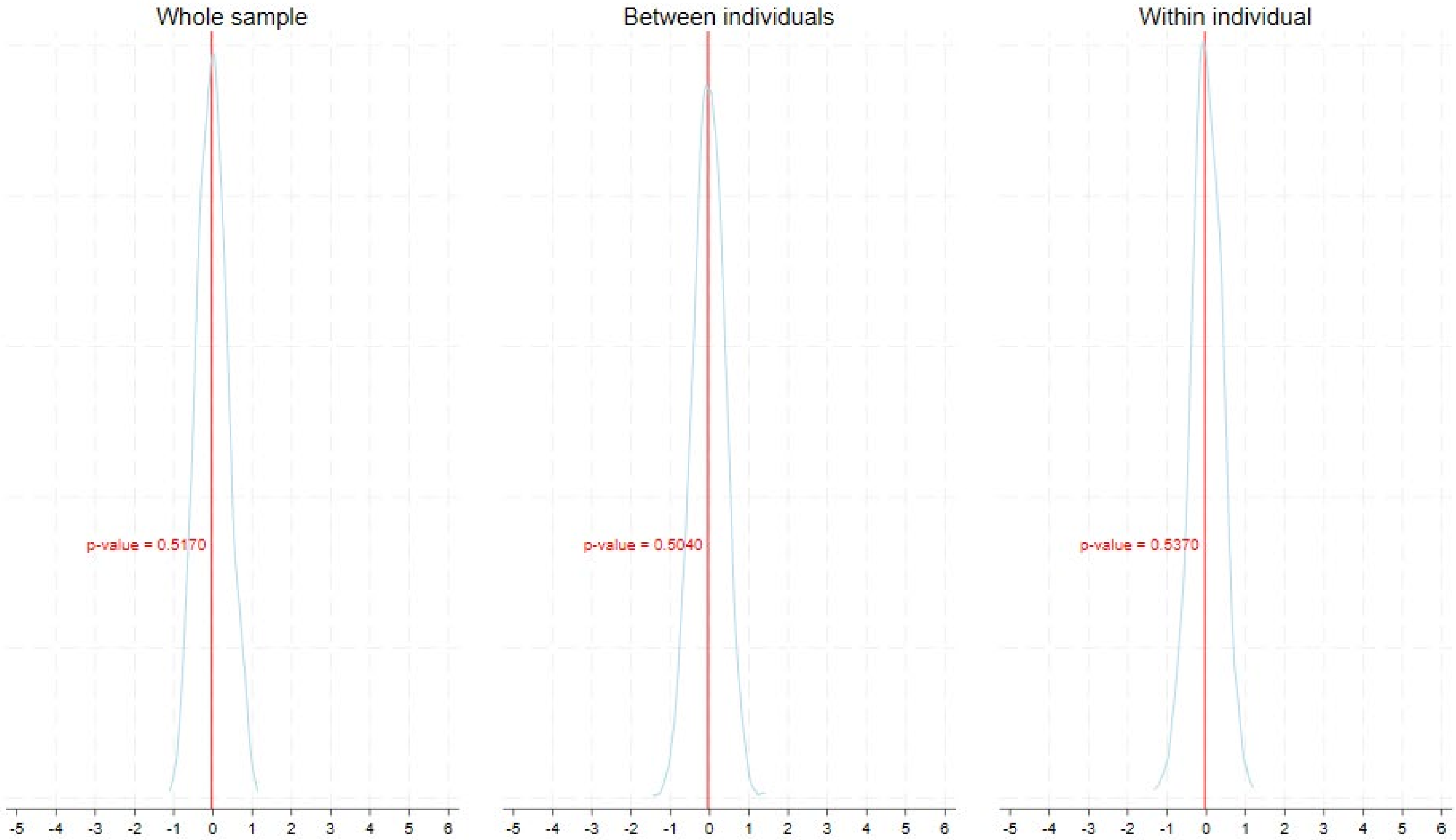
Notes: Data from historical tropical cyclone observed from 2011 to November 2023 and HILDA Release 22 (from Wave 12 onwards). The vertical dashed-dotted green line indicates the start of the financial year in Australia.

Appendix Figure A6: Distribution of maximum wind speed



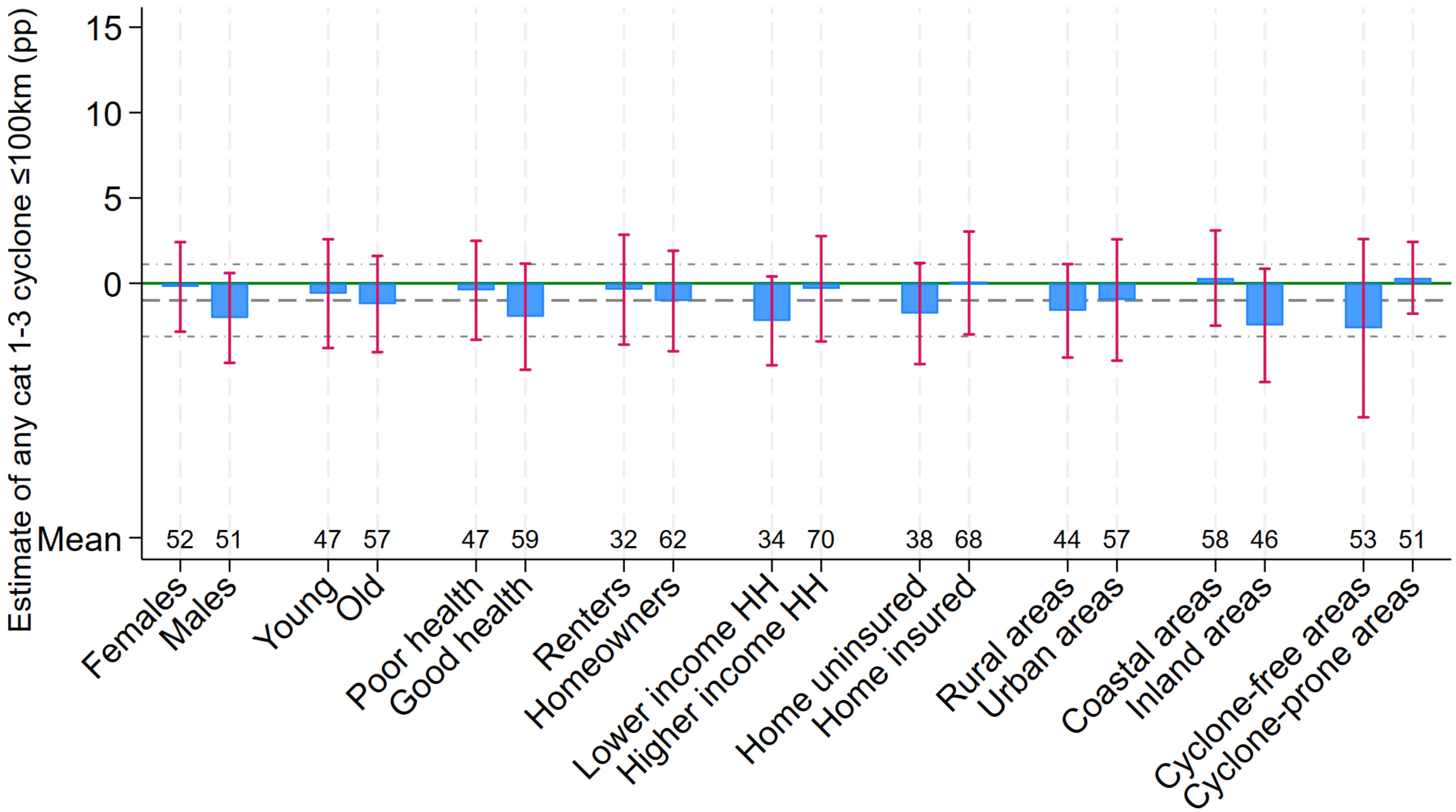
Notes: This figure illustrates the distribution of wind speeds across all years for individuals in our final sample who have ever been exposed to a cyclone within 100 km of their residential postcode centroid. The vertical dashed-dotted green lines represent the maximum mean wind speed thresholds prescribed by the Australian Bureau of Meteorology for identifying cyclone categories.

Appendix Figure A7: Randomization tests for exposure to a category 1 to 4 cyclone within 100 km of its eye



Notes: This figure illustrates the distribution of 1,000 regression estimates of the cumulative effect of random assignment of exposure to a category 1 to 4 cyclone within 100 km of its eye. Individuals exposed to a category 5 cyclone within the same radius are excluded from this analysis. The vertical red line indicates the observed cumulative effect of exposure to a category 1 to 4 cyclone within 100 km of its eye, as obtained from real data. The transformed regression specified in Equation (2) is utilized in this experiment. The p-value is calculated as the probability that the estimate from the real data is greater than or equal to the estimates from the randomized data.

Appendix Figure A8: Heterogeneity in the cyclone impact on private patient hospital cover uptake – Exposure to any category 1 to 3 cyclone



Notes: Results for different sub-populations are obtained from a separate FE regression. The estimated effect represents the cumulative impact of both current and lagged cyclone exposure on current PPHC enrolment. Dependent variable: private patient hospital cover. Cyclone exposure measure: Any category 1 to 3 cyclone within 100 km. Individuals exposed to a category 4 or 5 cyclone within the same radius are excluded from this analysis. 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 dependent variable for each sub-population printed below the bars.