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Fertility responses to tropical cyclones: Causal evidence and mechanisms

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

In light of growing concerns over escalating natural disaster risks and persistently low fertility rates, this paper quantifies the causal impacts of tropical cyclones and identifies the pathways through which they influence childbearing decisions among Australians of reproductive age. Using an individual fixed effects model and exogenous variation in cyclone exposure, we find a robust and substantial decline in fertility, occurring only after the most severe category 5 cyclones, with the effect weakening as distance from the cyclone's eye increases. We find no evidence of delayed cyclone effects, indicating that the fertility loss attributable to these most severe cyclones is permanent. Our findings are robust to extensive validity checks, including a falsification test and various randomization tests. The fertility decline is most pronounced among younger adults, individuals with lower educational attainment, those childless at baseline, and those lacking prior private health or residential insurance. While physical health, financial constraints, and migration appear unlikely to drive the effect, the evidence points to reduced family formation, increased marital breakdown, child mortality, cyclone-induced home damage, elevated psychological stress, and heightened risk perceptions as plausible mechanisms.

Keywords: Natural Disasters; Cyclones; Fertility; Marriage; Australia

JEL classifications: J12; J13; Q54

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1. Introduction

Natural disasters significantly disrupt lives, posing challenges beyond immediate relocation and health concerns (Dell *et al.* 2014; Carleton & Hsiang 2016; Carleton *et al.* 2022). Given the profound influence of childbearing on individuals, families and society (Becker 1960; Doepke *et al.* 2023), projected increase in the frequency and intensity of natural disasters (Elsner *et al.* 2008; Knutson *et al.* 2010), and persistently low fertility rates (Bloom *et al.* 2024; Goldin 2025), understanding the effects of natural disasters on fertility is critical.

Despite growing interest among the public, policymakers, and researchers, robust causal evidence on the impact of natural disasters on fertility remains scarce (see Lee *et al.* (2023) and Section 2 for a review of the literature). Existing studies primarily rely on macro-level data or individual-level data lacking a temporal dimension. These limitations hinder efforts to account for unobserved individual characteristics, including residential preferences, that are constant over time and may influence both natural disaster exposure and fertility decisions (Graff Zivin & Neidell 2013; Dell *et al.* 2014; Botzen *et al.* 2019). This is concerning as prior research suggests individuals residing in disaster-prone areas tend to have distinct socioeconomic backgrounds (Currie & Rossin-Slater 2013; Nguyen & Mitrou 2025d). Consequently, the validity of existing findings hinges on addressing these unobserved factors.

Furthermore, the current literature often employs natural disaster exposure measures that depend on human behaviours, potentially biasing the estimates of natural disaster effects (Wooldridge 2010; Botzen *et al.* 2019). These issues, in isolation or combined, undermine the causal interpretation of existing findings. Additionally, the literature lacks robust evidence on the potential mechanisms through which natural disasters may affect fertility (Doepke *et al.* 2023; Lee *et al.* 2023; Fontaine *et al.* 2024).

This study aims to bridge the gap in understanding how natural disasters causally impact fertility and the potential mechanisms at play. We leverage a unique dataset—over two decades

of nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, linked with historical tropical cyclone records. By employing exogenously measured cyclone exposures and utilizing individual fixed-effects models, we isolate the causal impact of tropical cyclones[1] (hereafter referred to as cyclones) on fertility decisions among Australians of reproductive age. This research design also enables us to investigate the potential pathways through which cyclones shape childbearing choices.

This study makes four key contributions to the existing literature. First, it presents the first comprehensive analysis of how cyclones affect fertility in Australia.[2] While cyclones are a significant natural hazard (Hsiang & Jina 2014; Nguyen & Mitrou 2025d), no prior Australian study has examined their impact—or that of other natural disasters—on fertility decisions. A focus on Australian fertility is particularly relevant because, like many developed countries (Bloom *et al.* 2024), Australia has been experiencing a continuous decline in its total fertility rate. Despite policy efforts to increase fertility, the rate remains well below the replacement rate (Gray *et al.* 2022). Understanding how cyclones influence fertility decisions is therefore essential not only for Australia but also for other countries with comparable socio-economic conditions or those experiencing similar natural disasters (Hsiang & Jina 2014; Carleton *et al.* 2022).

Second, this study pioneers the use of longitudinal individual-level data and exogenously constructed natural disaster exposure measures to examine the causal effects of natural disasters on fertility. The HILDA dataset allows us to employ an individual fixed-effects

[1] Our study focuses on Australia, where this weather phenomenon is regionally referred to as a "tropical cyclone" or, alternatively, a "cyclone". Other region-specific terms for the same phenomenon include "hurricane" and "typhoon" (Bureau of Meteorology (BOM), 2025).

[2] This study builds on previous Australian research utilizing the same dataset and employing largely similar methodologies to examine the effects of natural disaster-related events, including cyclones, on various outcomes such as residential choices (Nguyen & Mitrou 2024b), life satisfaction (Nguyen & Mitrou 2024a), locus of control (Nguyen & Mitrou 2025b), and the demand for health insurance (Nguyen & Mitrou 2025d). However, none of these studies have exclusively investigated the effects of cyclone exposure on fertility outcomes, as this study does.

model, effectively controlling for unobserved individual time-invariant factors (Dell *et al.* 2014; Auffhammer 2018; Botzen *et al.* 2019). Moreover, our study utilizes various exogenous cyclone exposure metrics, combining the distance from the individual's residential postcode centroid to the eye of the cyclone and the cyclone category. This empirical strategy addresses potential biases from unobserved individual factors and facilitates a novel investigation of the dynamic impacts of cyclones on fertility. A robust examination of the causal impact of natural disasters on fertility is particularly important given growing concerns over escalating natural disaster risks, persistently low fertility rates, the ambiguous potential effects suggested by existing theoretical frameworks (Doepke *et al.* 2023; Fontaine *et al.* 2024), and the mixed findings in the international literature (Lee *et al.* 2023).

Third, our extensive longitudinal data enables an exceptionally rich heterogeneous analysis. Spanning 23 years and encompassing over 100 cyclones of varying severity, the dataset offers a unique opportunity to explore the differential impacts of cyclones. This breadth allows us to generalize findings across cyclones of varying severity and examine impacts across diverse subpopulations, defined by a range of individual and household characteristics. This comprehensive analysis elucidates potential channels through which cyclones influence fertility and identifies vulnerable groups and regions for targeted support and resilience-building strategies (Carleton *et al.* 2022).

Fourth, this study advances the field by comprehensively exploring potential pathways through which cyclones influence fertility. By employing an individual fixed-effects model, we examine the effects of cyclones on numerous factors impacted by cyclone exposure and associated with childbearing decisions. These include mortality, financial factors, infrastructure damage, displacement, partnership dynamics, and psychological stress (Becker & Barro 1988; Doepke *et al.* 2023; Lee *et al.* 2023). Most of these pathways are not formally validated in the literature due to data limitations or the absence of robust empirical models (Lee

et al. 2023). The more robust evidence provided in this study, both on the fertility impacts of tropical cyclones and on the mechanisms underlying these effects, also has important implications for international research documenting substantial increases in mortality following tropical cyclones (Anttila-Hughes & Hsiang 2013; Huang *et al.* 2023; Young & Hsiang 2024). In particular, failing to account for fertility changes may lead to biased estimates of mortality. Furthermore, this original investigation of the mechanisms linking cyclones and fertility offers valuable insights for policy design aimed at mitigating the devastating impacts of natural disasters and supporting fertility.

Our empirical analysis yields four main findings. First, the individual fixed-effects model reveals a statistically significant, though transient, decline in fertility attributable to cyclone exposure. This effect is limited to category 5 cyclones—the most severe, with maximum wind speeds of at least 199 km/h—and attenuates with greater distance from the cyclone's eye. We find no evidence of delayed effects of cyclones, suggesting that the fertility loss attributable to these most severe events is permanent. The largest effect—a 3.75 percentage point reduction in the probability of having a newborn, equivalent to approximately 67% of the sample mean—is observed among individuals exposed to a category 5 cyclone within 30 km of its eye in the 12 months preceding the survey. Notably, the magnitude of this effect is comparable to, or even larger than, the documented fertility declines associated with job displacement in Austria (Del Bono *et al.* 2012) or the removal of a universal child benefit in Spain (González & Trommlerová 2023).

Second, the robustness of our findings is reinforced through rigorous scrutiny using various sampling strategies, model specifications, and fertility measures. Additional confirmation is provided by a falsification test, which demonstrates that future cyclones do not influence current fertility decisions, along with multiple randomization tests. Moreover, results from a series of robustness checks indicate that neglecting to account for individual time-invariant

unobserved factors—as has been the case in much of the prior literature—may lead to an overestimation of the attenuating effect of cyclones on fertility by approximately 8%.

Third, extensive heterogeneity analyses reveal significant variation in the fertility response to cyclone exposure across subpopulations. The decline is most pronounced among younger individuals, the less educated, the childless at baseline, those without prior private health insurance, and households without prior residential insurance.

Fourth, the study offers suggestive evidence on the pathways through which cyclone exposure may reduce fertility. Likely channels include reduced family formation, increased marital dissolution, child mortality, cyclone-induced home damage, elevated psychological stress, and heightened risk perceptions. By contrast, individual physical health, financial constraints, and relocation appear unlikely to be significant mediating factors in this context.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature, while Section 3 describes the primary data sources employed in this study. Section 4 details the main empirical model used to quantify the causal impact of cyclones on fertility. Section 5 presents the core empirical results. Section 6 explores the robustness of our findings through a series of sensitivity tests. Section 7 examines the heterogeneous impacts of cyclones across different subgroups of the population. Section 8 investigates potential mechanisms underlying our findings. Finally, Section 9 concludes the paper.

2. Literature review

This study investigates the impact of cyclone exposure on fertility among Australians, contributing to the burgeoning literature on the socio-economic consequences of natural disasters (Dell *et al.* 2014; Botzen *et al.* 2019).[3] Within this broader field, our research aligns

[3] Our research is also connected to studies examining the impacts of cyclones, hurricanes, and typhoons on various outcomes, including migration (Mahajan & Yang 2020; Sheldon & Zhan 2022; Nguyen & Mitrou 2024b), economic outcomes (Hsiang & Jina 2014; Deryugina 2017; Gallagher & Hartley 2017; Deryugina *et al.* 2018; Groen *et al.* 2020; Brannlund *et al.* 2023), and health outcomes (Anttila-Hughes & Hsiang 2013; Currie & Rossin-

more closely with a smaller but expanding body of work examining the effects of natural disasters on fertility decisions (see Lee *et al.* (2023), for a recent review).[4]

Several theoretical models potentially explain fertility behaviours in response to natural disasters (for a review of the general economics of fertility, see Doepke *et al.* (2023), or for a more detailed discussion of theoretical models explaining the mechanisms behind the impacts of natural disasters on fertility, see Fontaine *et al.* (2024)). For instance, the seminal quality–quantity model developed by Becker (1960) predicts a negative relationship between income and fertility, implying that natural disasters, which are assumed to reduce income, would be expected to lower fertility. By contrast, extensions of the quality–quantity model, such as that proposed by Pörtner (2001), incorporate uncertainty about future income and child survival, predicting that natural disasters—which are expected to increase child mortality—may lead to higher fertility due to a "replacement" effect (Doepke 2005). Moreover, as discussed and modelled by Fontaine *et al.* (2024), the insurance strategy framework of Pörtner (2001) can be used to predict a decrease in fertility, as natural disasters may increase uncertainty about future income, thereby reducing fertility.

Relatedly, Schmidt (2008) incorporates risk preferences and uncertainty into models of fertility decisions, predicting that during periods of heightened uncertainty—such as exposure to natural disasters—risk-averse individuals are more likely to postpone childbearing than risk-tolerant individuals. This suggests a negative impact of natural disasters on fertility, particularly among the risk-averse. Overall, while no single theoretical framework exclusively models the impact and pathways through which natural disasters affect fertility, existing

Slater 2013; Bakkensen & Mendelsohn 2016; Deryugina & Molitor 2020; Parks *et al.* 2021; Carleton *et al.* 2022; Huang *et al.* 2023; Parks *et al.* 2023).

[4] This study also contributes to the broader literature on the determinants of fertility (see Doepke *et al.* (2023), for a recent review). This literature has explored the fertility impacts of various factors, including income (Alam & Pörtner 2018), employment (Huttunen & Kellokumpu 2016), education (McCrary & Royer 2011), macroeconomic conditions (Buckles *et al.* 2020), wars and conflicts (Abu-Musa *et al.* 2008; Guerra-Cújar *et al.* 2024), and public policies (Gans & Leigh 2009; Lalive & Zweimüller 2009; Brewer *et al.* 2012; Deutscher & Breunig 2018; Grossman *et al.* 2025).

frameworks suggest a potentially mixed response. Consequently, the effect of natural disasters on fertility remains an empirical question.

Prior empirical research within this domain has explored the fertility impacts of diverse natural disasters, including hurricane risks (Pörtner 2008), storm advisories (Evans *et al.* 2010), floods (Tong *et al.* 2011), climate shocks related to temperature and precipitation (Sellers & Gray 2019), earthquakes (Finlay 2009; Nandi *et al.* 2018), tsunami (Nobles *et al.* 2015), combined earthquake and tsunami events (Hamamatsu *et al.* 2014; Kurita 2019; Körblein 2021), cyclones/hurricanes/typhoons (Cohan & Cole 2002; Davis 2017; Seltzer & Nobles 2017; Fontaine *et al.* 2024), and multiple natural disasters and epidemics (Norling 2022).

Many of these studies utilize data from developing countries, including Guatemala (Pörtner 2008), Indonesia (Nobles *et al.* 2015; Sellers & Gray 2019), Nicaragua (Davis 2017), India (Nandi *et al.* 2018), a combined sample of India, Pakistan, and Turkey (Finlay 2009), 33 African nations (Norling 2022), and six developing countries (Fontaine *et al.* 2024).[5] By focusing on Australia, a developed nation, this study aligns more closely with research employing data from other developed countries, specifically the United States (Cohan & Cole 2002; Evans *et al.* 2010; Tong *et al.* 2011; Seltzer & Nobles 2017) and Japan (Hamamatsu *et al.* 2014; Kurita 2019; Körblein 2021).

The existing literature on the relationship between natural disasters and fertility yields mixed results, aligning with the predictions from the theoretical models discussed above. Some studies suggest that natural disaster exposure reduces fertility (Tong *et al.* 2011; Hamamatsu *et al.* 2014; Kurita 2019; Körblein 2021; Fontaine *et al.* 2024), while others report the opposite effect (Cohan & Cole 2002; Pörtner 2008; Finlay 2009; Nobles *et al.* 2015; Davis 2017; Nandi *et al.* 2018). Additionally, several studies present mixed findings contingent on the

[5] These countries include Bangladesh, Cambodia, Dominican Republic, Haiti, Madagascar, and the Philippines.

characteristics of the disaster and the surveyed population (Evans *et al.* 2010; Seltzer & Nobles 2017; Sellers & Gray 2019; Norling 2022).

Two primary shortcomings limit the causal interpretability of existing research on natural disasters and fertility.[6] The first limitation stems from data choices. Most studies, including all those from developed countries,[7] rely on macro-level data or cross-sectional individual-level data. These data structures lack the ability to account for unobserved time-invariant individual characteristics that may influence both natural disaster exposure and fertility decisions. Only a handful of studies utilize cross-sectional individual-level data, exclusively from developing countries (Finlay 2009; Nobles *et al.* 2015; Nandi *et al.* 2018; Norling 2022; Fontaine *et al.* 2024).[8] However, the cross-sectional nature of these datasets prevents the application of individual fixed-effects models, which are necessary to control for such unobservable factors. Consequently, these studies often aggregate fertility data to a spatial level (e.g., district) and employ Difference-in-Differences (DID) models to estimate the impact of natural disasters (Finlay 2009; Nandi *et al.* 2018; Norling 2022).

The second limitation concerns the use of natural disaster exposure measures that depend on human behaviours, potentially biasing the estimated effects (Wooldridge 2010; Dell *et al.* 2014; Botzen *et al.* 2019). Examples include classifying regions as disaster-affected based on official declarations (Cohan & Cole 2002) or utilizing damage incurred by the disaster, either at the individual level (e.g., child death) or region level (e.g., number of deaths) (Nobles *et al.* 2015; Norling 2022). Exceptions to the reliance on behavioural measures include Davis (2017),

[6] For a comprehensive assessment of econometric models used to estimate the effects of natural disasters, see surveys by Auffhammer (2018) or Botzen *et al.* (2019).
[7] Specifically, US studies typically employ county-level data (Cohan & Cole 2002; Evans *et al.* 2010; Seltzer & Nobles 2017) while Japanese studies primarily employ prefecture-level data (Hamamatsu *et al.* 2014; Kurita 2019; Körblein 2021).
[8] Two notable exceptions are Nobles *et al.* (2015) and Sellers and Gray (2019), who utilize individual panel data from Indonesia to examine the effects of mortality caused by the 2004 Indian Ocean tsunami and climate shocks related to temperature and precipitation, respectively, on mothers' fertility. However, their models do not account for individual fixed effects.

who uses satellite-derived precipitation data to proxy for Hurricane Mitch exposure in Nicaragua, and Fontaine *et al.* (2024), who employ calculated maximum surface wind speed for tropical cyclone exposure.

In conclusion, the two aforementioned limitations – data choices and exposure measures – independently or together, hinder the causal interpretation of existing research on natural disasters and fertility (Wooldridge 2010; Dell *et al.* 2014; Botzen *et al.* 2019).[9] Furthermore, prior studies employing cross-sectional individual-level data were unable to examine the dynamic effects of natural disasters on fertility decisions at the individual level, as this study achieves. Additionally, while some studies have hypothesized potential mechanisms underlying their findings (see Lee *et al.* (2023), for a review), none have definitively established these pathways, likely due to data constraints or limitations within their empirical models. This study addresses these shortcomings.

3. Data and sample

3.1. Data

This study leverages data from two primary sources. The first source is the Household, Income and Labour Dynamics in Australia (HILDA) survey, as detailed in the data manual by Summerfield *et al.* (2024). HILDA is a nationally representative longitudinal survey launched in 2001, encompassing an initial sample of more than 7,000 households and over 19,000 individuals. This survey tracks individuals aged 15 and above residing in private households

[9] An exception is a recent study by Fontaine *et al.* (2024), which utilizes cross-sectional individual-level data from six developing countries, employs an exogenous measure of cyclone wind speed, and implement a mother fixed-effects model. Given the cross-sectional nature of their datasets, they rely on historical fertility information (e.g., children's year of birth and women's age at childbirth) to construct their (yearly) fertility measure. However, as they acknowledge, this approach necessitates strong assumptions, including the absence of disaster impacts on factors influencing childbearing decisions, such as migration, income, or health. The validity of these assumptions is questionable given the well-documented socio-economic consequences of natural disasters, particularly in less developed countries (Dell *et al.* 2014; Botzen *et al.* 2019).

on an annual basis. HILDA offers a rich dataset encompassing individual and household-level information, including residential details, fertility, health, and labour market outcomes.

A key advantage of the HILDA dataset is its ability to track individuals who relocate. This feature enables the observation of individuals both before and after cyclone events, allowing for the application of an individual fixed-effects regression model to rigorously estimate the causal impact of cyclones on fertility. Moreover, the richness of the HILDA data, combined with our access to its "Restricted" version—which includes the most detailed geographical identifiers at the postcode level[10] when linked with the historical cyclone dataset—facilitates a comprehensive analysis of the potential channels through which cyclones influence fertility. For this study, we utilize the latest release of HILDA, encompassing 23 waves of data spanning the period from 2001 to 2023.

The second data source is a publicly available historical cyclone database maintained by the Australian Bureau of Meteorology (BOM). This database offers comprehensive information on all tropical cyclones occurring south of the equator between longitudes 90E and 160E (BOM 2025). For each recorded cyclone, the database includes details such as the track (longitude, latitude, and time) and measures of cyclone strength, including wind speed.

We integrate these two datasets by matching the cyclone track (including location and timing) from the historical cyclone database with the individual's residential postcode centroid and

[10] According to the 2021 Census, each postcode area in Australia has an average population of approximately 9,500 individuals, spread across more than 2,500 postcode areas. Access to the Restricted HILDA dataset requires a special application, as it includes more detailed geographic identifiers than the General HILDA dataset, which lacks such granularity (Summerfield *et al.* 2024). However, the finest geographic identifier available in HILDA—the postcode—does not offer the geographic precision necessary to assess the effects of certain natural disasters, such as floods or storm surges. Conducting such an analysis would require a more precise geographic identifier, such as geocoded household addresses. Consequently, a comprehensive examination of the impacts of these natural disasters is left for future research.
In this study, cyclone severity is primarily measured using maximum mean wind speed and distance to the cyclone eye, without accounting for other co-occurring but currently unobserved hazards, such as torrential rain, flooding, and storm surges. Isolating these factors would require finer geographic detail than is available in the current data. This approach has been widely adopted in previous international studies, potentially for similar reasons (Mendelsohn *et al.* 2012; Currie & Rossin-Slater 2013; Hsiang & Jina 2014; Franklin & Labonne 2019; Parks *et al.* 2021).

interview date from the HILDA survey. We utilize the restricted version of HILDA containing postcodes, as they provide the highest level of geographical granularity available within the survey. A map depicting cyclone impacts during the study period is presented in Appendix Figure A1. This map reveals two key patterns. First, cyclones are spatially clustered in the northern states and territories of Australia. Second, although cyclones are relatively rare in Australia, the 23-year study period includes over 100 cyclones of varying severity, providing sufficient variation to detect potential effects.

3.2. Cyclone exposure measures

Following the methodology established in international and Australian studies that utilize panel individual-level data to examine the effects of cyclones on outcomes other than fertility (Currie & Rossin-Slater 2013; Henry *et al.* 2020; Nguyen & Mitrou 2025d), we employ a measure of an individual's annual exposure to local cyclones, incorporating both the cyclone's intensity category and proximity to its eye. First, following prior research (Hsiang & Narita 2012; Hsiang & Jina 2014; Deryugina 2017; Franklin & Labonne 2019; Huang *et al.* 2023; Parks *et al.* 2023; Fontaine *et al.* 2024; Nguyen & Mitrou 2025d) we measure cyclone exposure based on its intensity category, ranging from 1 (weakest) to 5 (strongest), using the BOM' prescribed cutoffs derived from maximum mean wind speeds (BOM 2025). Specifically, the maximum mean wind speed thresholds (in km/h) for cyclone categories 1 through 5 are as follows: ≤88, >88 and ≤117, >117 and ≤159, >159 and ≤199, and >199, respectively.[11]

We adopt these wind speed cutoffs suggested by the BOM, which are more commonly used in the Australian context of this study, for three primary reasons. First, as demonstrated in Appendix Figure A4, which illustrates the distribution of wind speeds for all cyclones affecting individuals in our sample, this categorization results in relatively balanced and sufficiently

[11] For a small subset of individuals (less than 3% of all affected individuals) experiencing multiple cyclones within a given year, we assign the cyclone with the highest category to represent their exposure.

large subgroups of individuals exposed to each cyclone category, thereby enabling robust estimation of the impacts of each category. Specifically, Appendix Figure A4 and Appendix Table A1 show that approximately 4% of individuals in our main sample were affected by a cyclone of any category within 100 km of its eye in the 12 months prior to the survey. Among these affected individuals, roughly 29%, 12%, 10%, 34%, and 15% were exposed to a cyclone of Category 1, 2, 3, 4, and 5, respectively. In absolute terms, the number of individuals affected by a cyclone of Category 1, 2, 3, 4, and 5—within the specified distance and time frame—is 1,571, 665, 551, 1,892, and 820, respectively.

Second, the use of wind speed cutoffs allows for a more flexible examination of potential non-linear effects of wind speed compared to methods imposing a predetermined functional form on the relationship between wind speed and fertility (Wooldridge 2010). Third, various international studies (Deryugina 2017; Franklin & Labonne 2019; Huang *et al.* 2023; Parks *et al.* 2023; Fontaine *et al.* 2024) have likewise employed wind speed thresholds—albeit with different cutoffs—to examine the potential non-linear impacts of cyclones on a range of socio-economic outcomes. In subsequent sections, we further explore potential non-linear effects of wind speed by considering alternative cutoffs and applying different functional forms.

Additionally, following previous studies (Currie & Rossin-Slater 2013; Franklin & Labonne 2019; Nguyen & Mitrou 2025d), we differentiate cyclone exposure by calculating the distance from the centroid of an individual's residential postcode to the cyclone's eye, defined as the central region of calm surrounded by the most destructive winds (BOM 2025). For the baseline analysis, we utilize a distance cutoff of 100 km, acknowledging the relatively infrequent occurrence of yearly cyclones within the study period. In subsequent analyses, we will apply alternative distance thresholds.

We utilize the precise HILDA interview dates, which may vary for individuals residing in the same postcode within a given survey wave, in conjunction with cyclone timing to calculate

exposure for each individual.[12] This matching procedure may result in differences in exposure to the same cyclone among individuals residing in the same postcode during a given survey year. This computationally intensive matching process enhances the robustness of our identification strategy by leveraging the exogenous temporal variation in cyclone exposure experienced by the same individuals over time.

3.3. Fertility measures

We measure fertility using a binary variable that takes the value of 1 if the individual has at least one child under the age of one at the time of the survey, and 0 otherwise (hereafter referred to as having a "newborn child" or a "birth"). This measure is constructed using the exact date of birth of each child—whether residing with or apart from the individual—and, as expected, the majority of newborns reside with the individual. The date of birth is matched to the date of the individual's interview (Summerfield *et al.* 2024). The variable is recorded annually and reflects the respondent's fertility status at the time of the interview.[13] It is available across all survey waves, thereby maximizing the number of observations for robust analysis. Alternative measures of fertility will be considered in subsequent sections, although some of these are not consistently available across all waves.

[12] For example, consider two individuals residing in the same postcode who are surveyed one month apart within a specific survey wave (e.g., one in October 2012 and the other in November 2012). If a cyclone occurred in October 2011, this discrepancy in survey timing would affect the measurement of both fertility outcomes and cyclone exposure. Fertility outcomes, recorded at the time of the survey as described below, and cyclone exposure, assessed over the 12 months preceding the survey date, would lead to differing classifications: the first individual would be categorized as affected by the cyclone in the 2012 survey year, whereas the second individual would not. It is important to note that we use precise HILDA interview dates, which provide a finer temporal resolution than the survey months illustrated in this example, leading to greater variation in exposure to the same cyclone among individuals residing in the same postcode.

[13] By construction, this indicator assigns a value of 1 to individuals with multiple births within the same year. However, such cases are extremely rare, representing only 0.09% of the sample, and are therefore insufficient for separate robust analysis. We make use of the restricted HILDA release, which includes the exact date of birth for all household members, whereas the general release provides only the year of birth, to construct this fertility measure. Moreover, for non-co-residing children, only the month and year of birth are available.

3.4. Sample

This study uses the individual as the primary unit of analysis, as the key outcome variable—fertility—is defined at the individual level. We focus on states and territories within Australia that experienced at least one cyclone during the study period (2001-2023). This selection strategy enhances the precision of individual fixed effects estimates for cyclone-exposed individuals (Wooldridge 2010). Consequently, our baseline sample comprises individuals residing in New South Wales, Queensland, Western Australia, and the Northern Territory. Appendix Figure A1 provides a visual representation of the geographic distribution of cyclone impacts during this period.

Furthermore, the main analysis explores fertility outcomes for both males and females, acknowledging fertility decisions as typically joint choices made by couples (Doepke & Kindermann 2019; Doepke *et al.* 2023; Bloom *et al.* 2024). This approach is supported by our data, in which, as noted above, fertility is reported separately for each individual, regardless of gender. Although the data include fertility information for all males and females aged 15 and above, irrespective of marital status, we deliberately restrict the analytical sample to individuals of reproductive age to ensure the robustness of the analysis. Specifically, the sample includes women within their childbearing years, defined for this study as the age range of 15 to 49 years. This age range aligns with prevalent practices in Australia and internationally (Bloom *et al.* 2024). For males, although a universally accepted maximum reproductive age does not exist, we adopt a slightly higher upper age limit of 54 years. This choice is informed by three key considerations. First, males generally exhibit a higher reproductive capacity compared to females (Billari *et al.* 2011). Second, our data align with the trend of females partnering with older males (Nguyen *et al.* 2024b). Third, the HILDA survey, from which our data originate, only collects certain fertility-related data for individuals aged under 55 (Summerfield *et al.* 2024).

In following sections, we will employ alternative age restrictions (in robustness checks) and explore potential differential impacts of cyclones on fertility outcomes by gender and marital status, among other socio-economic characteristics (in heterogenous analysis). An additional criterion for inclusion in the sample is observation on at least two occasions during the study period. This requirement stems from the reliance of our primary empirical model on individual fixed effects. By applying these criteria, the final dataset employed for the primary analysis encompasses over 133,000 individual-year observations derived from more than 14,000 distinct individuals observed over a 23-year period.

4. Empirical model

Following the methodology employed in prior studies that examine the effects of natural disasters using individual-level panel data (Currie & Rossin-Slater 2013; Henry *et al.* 2020; Nguyen & Mitrou 2025d), we utilize an individual fixed-effects (FE) model to estimate the causal impact of cyclones on fertility outcomes. The model is specified as follows:

$$Y_{ipt} = \alpha + \sum_{L=1}^{k} [Z_{ip(t-L)}\boldsymbol{\beta}_L] + X_{ipt}\boldsymbol{\gamma} + \lambda_t + M_{it} + \delta_p + \pi_i + \varepsilon_{ipt} \qquad (1)$$

In Equation (1), Y_{ipt} represents the fertility outcome for individual i living in postcode p at survey time t. The key explanatory variable, $Z_{ip(t-L)}$, captures cyclone exposure, defined as a categorical variable indicating whether individual i experienced a cyclone of category 1, 2, 3, 4 or 5 (with unaffected individuals serving as the reference group) within their postcode during various time windows.

To account for temporal variations in cyclone exposure and fertility outcomes, we include separate controls for survey year (λ_t) and survey month (M_{it}). As illustrated in Appendix Figure A3, the distribution of cyclone occurrences and HILDA interview dates displays distinct seasonality during the study period. A significant proportion of HILDA interviews (92%) were conducted from August to October, whereas nearly all cyclones (96%), across all categories,

occurred between November and April. This temporal separation minimizes the potential influence of immediate pre-cyclone interviews on fertility outcomes measured in subsequent survey waves. To address this seasonal pattern, we include survey month dummies in all regressions. Additionally, as detailed in Subsection 3.2, differences in survey dates among individuals residing within the same postcode may result in variations in exposure to the same cyclone within a single survey year.

We also control for regional heterogeneity using postcode fixed effects (δ_p). This is particularly important given the variation in size and distribution of Australian postcode boundaries, as shown in Appendix Figure A2. Relying solely on postcode centroids to estimate proximity to cyclone paths could misrepresent individuals' exposure. By including postcode fixed effects, we address this potential data limitation and control for time-invariant factors at the postcode level.

In the baseline analysis, we include a limited set of variables in the vector of time-varying control variables (X_{it}) to avoid the "bad control" problem, whereby some controls may be related to fertility decisions and contemporaneously affected by cyclone exposure, potentially biasing the estimates of both cyclone exposure and these controls (Angrist & Pischke 2009). Specifically, X_{it} includes individual characteristics such as age group (measured in five-year intervals, e.g., 15–19, 20–24, and so on), education level, and residence in a major city. Moreover, to account for local socio-economic contexts that may influence fertility decisions, we incorporate two time-varying regional variables at the Local Government Area (LGA) level: unemployment rates and Socio-Economic Indexes for Areas (SEIFA).

The individual FE approach is critical in this analysis as it accounts for unobserved, time-invariant individual characteristics (π_i) that may be correlated with both cyclone exposure and fertility outcomes. This is particularly relevant given previous research suggesting a link between pre-existing disadvantage and residence in disaster-prone areas (Currie & Rossin-

Slater 2013; Nguyen & Mitrou 2025d). In this model, $\alpha, \boldsymbol{\beta}_L$ and $\boldsymbol{\gamma}$ are parameters to be estimated, with $\boldsymbol{\beta}_L$ representing the parameters of interest. These estimates capture the causal impact of cyclones by leveraging within-individual, within-postcode variations in cyclone exposure over time. The inherent stochastic nature of cyclone impacts, despite potential spatial clustering, further enhances the internal validity of our causal inference.

We begin by examining the effect of cyclone exposure—measured within the 12 months preceding the interview date ($L = 1$)—on fertility recorded at the time of the survey. This timeframe, consistent with the annual frequency of our survey, allows sufficient time for the immediate effects of cyclones on fertility to materialize. We subsequently explore potential lagged effects by incorporating k lags of cyclone exposure alongside current exposure. The optimal lag length (k) will be determined empirically based on the data and the applied models.

This study exploits unique long-term individual panel data to assess the delayed effects of cyclone exposure by introducing lagged measures of exposure, together with contemporaneous exposure, into the regression of current fertility. This dynamic specification acknowledges that fertility decisions involve both planning and gestation periods, and thus allows us to capture delayed cyclone effects that may take time to become apparent. Furthermore, it allows for a novel investigation into whether cyclones result in the postponement of pregnancies—and thus births—that may subsequently be recuperated. If such postponement occurs following an initial fertility decline, we would expect a positive and statistically significant coefficient on lagged cyclone exposure in the fertility regression. This finding would have important policy implications, as it would inform whether fertility losses due to cyclones are temporary or permanent (Hsiang & Narita 2012; Carleton *et al.* 2022).

To estimate our individual FE model, we employ Ordinary Least Squares (OLS) regression. As is common in the empirical literature addressing binary dependent variables in longitudinal data settings (Currie & Rossin-Slater 2013; Fontaine *et al.* 2024), we use a FE linear probability

model (LPM) rather than a FE logit model due to its simplicity and practical advantages.[14] Moreover, to address potential serial correlation, we cluster standard errors at the postcode level (Cameron & Miller 2015).

5. Main results on impacts of cyclone exposure on fertility

5.1. Descriptive results

Table 1 provides descriptive statistics for key variables, stratified by cyclone exposure status. Approximately 4.12% of individuals, representing the "treated" group—equivalent to 5,499 year-observations from 3,840 unique individuals—experienced at least one cyclone within a 100 km radius of their residence during the study period. As shown in Appendix Table A1, despite the relatively infrequent occurrence of cyclones during the study period, the sample includes a substantial number of individuals exposed to various cyclone categories, enabling credible detection of potential effects.

While no statistically significant differences are observed between the two groups in terms of age, gender, or marital status, those impacted by cyclones are less likely to be foreign-born from a Non-English Speaking Background (NESB) country or reside in a major city.[15] This pattern aligns with previous research suggesting a tendency for NESB migrants to concentrate in major metropolitan areas, which are generally less susceptible to cyclones owing to most of them being situated at latitudes south of typically cyclone-prone regions, compared to Australian-born individuals or migrants from English Speaking Background (ESB) countries

[14] Specifically, the LPM retains all observations and allows straightforward estimation of individual fixed effects, whereas fixed effects logit models are computationally intensive and exclude individuals with no variation in the outcome (Wooldridge 2010). Moreover, LPM coefficients are directly interpretable as changes in probability, making the results more accessible. While it may yield predicted probabilities outside the [0,1] range, this is typically a minor issue in large samples like ours (Angrist & Pischke 2009).

[15] For illustrative purposes and completeness, we present statistics for time-invariant variables such as gender and migration status in this section. While these variables are excluded from individual FE regressions, as will be detailed in following sections, they will be included in regressions that do not control for individual fixed effects.

(Nguyen & Duncan 2017). This highlights the importance of accounting for residential selection when examining the impact of cyclones on individual behaviours.

Cyclone-affected individuals also exhibit lower educational attainment, as measured by a lower likelihood of holding a bachelor's degree or higher. Furthermore, they tend to reside in regions characterized by lower overall socioeconomic status, as indicated by a lower SEIFA index. The observation that individuals with lower educational attainment or residing in regions with lower socioeconomic conditions are more likely to be affected by cyclones is consistent with prior Australian and international research (Currie & Rossin-Slater 2013; Nguyen & Mitrou 2025d). In contrast, cyclone affected individuals are more likely to reside in regions with a lower unemployment rate. These contrasting socioeconomic characteristics between cyclone-affected and unaffected areas further emphasize the importance of accounting for unobserved individual-level factors, such as residential preferences, when quantifying the impact of natural disasters on human behaviours.

Table 1, along with Appendix Table A1, presents descriptive statistics indicating that, on average, individuals in our sample have 1.22 living children, and approximately 6% reported having a newborn at the time of the survey (our primary measure of fertility). Furthermore, there is no statistically significant difference between cyclone-affected and unaffected individuals in either the number of living children or the likelihood of having a newborn. However, as elaborated upon in Section 4, this statistically insignificant relationship between cyclone exposure and fertility does not account for time-varying and time-invariant factors that may be correlated with both exposure and fertility outcomes. Subsequent analyses address this critical issue.

5.2. Main regression results

Table 2 presents the estimates for various measures of cyclone exposure recorded at different time windows, obtained from our preferred individual FE regression models.[16] These models account for both observable time-varying and unobservable time-invariant factors that may influence fertility outcomes. Column 1 of Table 2 reports the results for cyclone exposure measured in the year preceding the survey, indicating a statistically significant ($p < 0.01$) negative association between exposure to category 5 cyclones and the likelihood of having a newborn. Specifically, individuals exposed to a category 5 cyclone within 100 km of their residence in the past 12 months are estimated to be 3.04 percentage points (pp) less likely to have a newborn. In contrast, exposure to cyclones of categories lower than 5 does not yield statistically significant estimates at any conventional significance level.

Recognizing the potential for a temporal lag between cyclone exposure and changes in fertility behaviour, we further examine the dynamic effects of cyclones on fertility decisions by incorporating lagged cyclone exposure measures into the regression model of current fertility. Column 2 of Table 2, which reports estimates for both concurrent and one-year lagged exposures, yields two key findings. First, the results for concurrent cyclone exposure remain consistent with the baseline estimates in Column 1—specifically, only the coefficient for concurrent exposure to category 5 cyclones is negative and statistically significant at the 1% level—thereby reinforcing the robustness of our conclusions. Second, all estimates for one-year lagged cyclone exposures are statistically insignificant, suggesting no delayed effect on fertility.

[16] Regression results for other key control variables are reported in Appendix Table A2. These findings are generally consistent with the international literature (Bloom *et al.* 2024). For example, we observe an inverted U-shaped relationship between fertility and age: fertility increases with age up to 35–39, then declines thereafter. Importantly, the estimates of these key control variables remain robust to a separate inclusion of variations in the cyclone exposure measure.

We next extend the model to include two-year lagged cyclone exposure measures. The results, presented in Column 3 of Table 2, again confirm a negative and statistically significant effect of current exposure to category 5 cyclones, while all lagged exposure measures remain statistically insignificant. Overall, the analysis provides no evidence of delayed effects, with the significant association between category 5 cyclone exposure and reduced fertility appearing to be concentrated in the contemporaneous period.[17] Given the absence of delayed effects for both category 5 and lower-category cyclones, the findings suggest that the fertility loss attributable to the most severe cyclones is permanent.

To further validate our findings, we conduct a falsification test using the individual FE model. This test rests on the assumption that future cyclone events, being inherently random and unexpected, should not affect current fertility outcomes, particularly when controlling for individual fixed effects and concurrent cyclone exposure. The falsification test includes lead (one year future) cyclone exposures alongside current exposure in the model.

The results, presented in Column 4 of Table 2, reveal two key patterns. First, the estimates for current cyclone exposures align with the baseline results, underscoring the robustness of our analysis. Second, all estimates for lead cyclone exposures are statistically insignificant, confirming that future cyclone events have no discernible influence on current fertility outcomes. These findings bolster the credibility of our causal inference.

The empirical findings thus far suggest that only the most severe category 5 cyclones, defined by maximum wind speeds of 199 km/h or higher, have a statistically significant negative impact on fertility. This result, which will be further substantiated in Subsection 6.2, underscores a pronounced non-linear relationship between cyclone intensity and childbearing decisions. To ensure clarity and conciseness, the remainder of this paper will primarily focus on results using

[17] We also experimented with excluding the current cyclone exposure measure from the regression of current fertility and found that the estimates of all lagged cyclone exposure measures remain statistically insignificant.

exposure to category 5 cyclones within 100 km of the cyclone's eye as the primary measure of cyclone exposure, unless otherwise specified. In particular, the categorical variable Z_{ijt} in Equation (1) is replaced with a binary variable indicating whether an individual experienced exposure to a category 5 cyclone. Moreover, we include only the concurrent exposure measure—defined as exposure to any category 5 cyclone within the 12 months preceding the survey—since previous results provide no evidence of delayed effects on fertility.

Column 5 of Table 2 reports the concurrent impact of exposure to a category 5 cyclone[18] on the likelihood of having a newborn, based on the modified regression specification. The estimated effect is a reduction of 2.92 pp, which is slightly smaller than the baseline estimate of 3.04 pp reported in Column 1—where a categorical cyclone exposure variable is employed—but remains highly statistically significant at the 1% level. This effect is still substantial, representing approximately 52% of the sample mean for the proportion of individuals reporting a newborn in the survey year, which is 5.6% (see last row of Column 5).

6. Robustness checks

6.1. Sample attrition issues

As with other studies utilizing survey data, a potential concern in this study is whether cyclone exposure influences participant retention. To examine this issue, we employ an individual FE model similar to Equation (1), where the primary dependent variable indicates whether an individual was not interviewed in the subsequent survey wave. Consistent with prior analyses, the key explanatory variables include current and one-year lagged indicators of cyclone exposure within a 100-km radius, along with other time-varying covariates specified in

[18] In this specification where we include only one dummy variable capturing concurrent exposure to any category 5 cyclone within a 100 km radius of its eye, we retain the sample size by not excluding individuals affected by cyclones of categories lower than 5. Consequently, the estimates compare individuals exposed to a category 5 cyclone with all other individuals, including those exposed to lower-category cyclones within a 100 km radius, who serve as the "control" group.

Equation (1). This model is applied to the baseline regression sample, consisting of individuals of reproductive age residing in historically cyclone-affected states or territories.

The results, presented in Appendix Table A4, reveal that the overall attrition rate in our sample is relatively low at 6.79%, aligning with the sampling statistics for the broader HILDA survey reported by Summerfield *et al.* (2024). Regression findings indicate statistically significant associations between certain demographic characteristics, such as age and education, and the likelihood of non-interview. However, the model demonstrates limited explanatory power, as indicated by an R-squared value of 0.04. Crucially, the estimates for the current and lagged cyclone exposure variables are individually and jointly statistically insignificant, as indicated by a p-value of 0.42 from a Wald test for the joint significance of all cyclone exposure variables. These results mitigate concerns about potential cyclone-induced sample selection bias in our analysis.

6.2. Further examinations of non-linearity in the cyclone impact

Baseline results using categorical cyclone exposure measures indicate a highly non-linear relationship, with statistically significant effects observed only for the most severe category 5 cyclones. This subsection further investigates potential non-linearities in the effects of wind speed by applying various functional forms and cutoffs. First, the five-category wind speed variable used in the baseline regression is replaced with wind speed included linearly as a continuous variable.[19] The results of this specification are presented in Column 1 of Appendix Table A3. Second, we introduce the derived wind speed variable in logarithmic, quadratic, and cubic forms (Columns 2, 3, and 4, respectively). Third, we include a dummy variable indicating whether an individual was affected by a cyclone of any category (Column 5). Fourth, instead

[19] Due to the absence of wind speed data for individuals not affected by cyclones, we assign an arbitrary value of one to these individuals. In this regression, and in all subsequent regressions employing this derived wind speed variable, we additionally incorporate a binary indicator variable to denote whether an individual was not exposed to a cyclone (Wooldridge 2010).

of 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 (Column 6).[20] In these experiments, as in the previous analyses, we include both concurrent and one-year lagged cyclone exposure measures to capture their potentially deferred effects on fertility outcomes.

Results from these experiments, reported in Appendix Table A3, show that estimates of wind speed variables in continuous form or when cyclone exposure is measured as a dummy variable are generally not statistically significant (see Columns 1 to 5). The only exception is a marginally statistically significant (at the 10% level) and negative estimate for current wind speed (Column 1), which suggests that the negative impact of a cyclone on fertility becomes stronger as wind speed increases. Specifically, the linear specification implies that, among individuals affected by any cyclone, a one km/h increase in wind speed is associated with a 0.0145 percentage point decrease in the probability of having a newborn child. The overall lack of strong statistical significance supports the use of a more flexible five-category wind speed variable in the main regression.

Additionally, employing 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 above) recorded concurrently have a statistically significant effect on reducing fertility (see Column 6). Overall, these robustness checks reinforce our primary finding that the effects of cyclones on fertility are significant only for the most severe category 5 cyclones, and that these effects are short-lived, as they are observed only when exposure occurs within 12 months prior to the measurement of fertility.

[20] We refrained from applying a more detailed categorization of wind speed because, as shown in Appendix Figure A4, this would result in subgroups of individuals exposed to each cyclone category that are too small for a robust analysis. Nevertheless, unreported results based on wind speed categorized into seven groups (in 25 km/h increments) indicate that only cyclones with the highest wind speeds (i.e., 200 km/h or above) have a statistically significant negative effect on fertility.

Our finding of highly non-linear impacts of wind speed is consistent with that in Nordhaus (2010), who showed that the macroeconomic impact of U.S. hurricanes is also highly non-linear, with catastrophic effects occurring above a certain wind speed threshold. Similarly, Mendelsohn *et al.* (2012) found that worldwide economic damages from tropical cyclones associated with forecasted climate change are highly non-linear with respect to cyclone severity, as proxied by wind speed, with the probability distribution of damages being heavily skewed and substantial losses concentrated in the tail of the distribution. These results align with recent Australian studies, which have shown that the impacts of cyclones on well-being and the demand for health insurance are concentrated among cyclones with exceptionally high wind speeds (Nguyen & Mitrou 2024a, 2025d). In this regard, our finding of non-linear cyclone impacts is consistent with related literature emphasizing the non-linearity of temperature effects on socio-economic outcomes (Burke *et al.* 2015; Carleton & Hsiang 2016). Moreover, our finding that tropical cyclones substantially reduce fertility only in the case of the most severe category 5 events—when viewed alongside projections of increasing cyclone intensity under global warming (Hoyos *et al.* 2006; Elsner *et al.* 2008; Mortlock *et al.* 2023) —is particularly relevant for policies aimed at mitigating the adverse impacts of climate change.

6.3. Other robustness checks

To enhance the robustness of our findings, we conducted a series of sensitivity analyses, incorporating variations in sampling strategies, model specifications, and fertility measures. For conciseness, we focus on the effects derived from concurrent exposure to any category 5 cyclone within a 100 km radius of its eye.

The first sampling test applies a narrower age restriction to address concerns regarding the adequacy of our baseline sample in capturing individuals of reproductive age. This sample includes both males and females aged 18 to 49 years. The estimated effect using this more restrictive age sample, shown in Panel A, Column 2 of Table 3, remains highly statistically

significant at the 1% level and exhibits a slightly larger magnitude (i.e., the cyclone effect is -3.39 pp, which is approximately 16% greater in absolute terms than the baseline estimate of -2.92 pp, re-reported in Panel A, Column 1). These results suggest that our baseline estimates are likely more conservative compared to those derived from an alternative sample with a narrower age restriction.

The second sampling test includes all individuals aged 15 and above in the fertility regression, enabled by the availability of fertility data for this age group. The results of this sensitivity analysis, presented in Panel A, Column 3, show statistically significant estimate ($p < 0.01$), though it is smaller in magnitude compared to the baseline estimate. Specifically, the effect of exposure to a category 5 cyclone within 100 km of its eye is estimated at -2.00 pp, representing 68% of the baseline estimate. The substantially lower reduction in fertility observed in the older sample aligns with the hypothesis that the primary impact of cyclones occurs among individuals of reproductive age (Billari *et al.* 2011), further supporting our choice of focusing on this demographic in the baseline sample.

The third sampling test includes only individuals of reproductive age residing in LGAs that were affected by at least one cyclone within 100 km during the study period, addressing concerns regarding the adequacy of cyclone exposure variation in the baseline sample. Results from this more geographically restricted sample, presented in Panel A, Column 4, show that the estimate is nearly identical to the baseline, despite the sample size being reduced by approximately half.

Conversely, we apply the same empirical model to a larger sample of individuals of reproductive age residing across all Australian states and territories. The estimated coefficient is slightly less negative in this exercise (−2.87 pp, as shown in Panel A, Column 5, representing 98% of the baseline estimate); however, the core finding—a statistically significant negative impact of cyclone exposure on fertility—persists, remaining significant at the 1% level.

In the above regressions, when we include only one dummy variable capturing concurrent exposure to any category 5 cyclone within a 100 km radius of its eye, we retain the sample size by not excluding individuals exposed to cyclones of lower categories. As an additional robustness check, we exclude individuals exposed to cyclones of categories 1–4 from the regression. The resulting estimate, reported in Panel A, Column 6, is slightly larger in absolute terms—by about 1%—than the baseline estimate (–2.94 compared to –2.92), while remaining statistically significant at the 1% level. This stability further supports the earlier finding that exposure to cyclones below category 5 has no statistically significant impact on fertility.

To isolate the potential influence of cyclones on migration, a factor identified in previous Australian research (Nguyen & Mitrou 2024b), the next sampling test excludes individuals who relocated between adjacent survey waves from the original sample. This approach aims to mitigate any confounding effects that migration decisions, potentially influenced by cyclones, may have on our fertility estimates. The resulting estimate from this specification, presented in Panel A, Column 7, remains statistically significant at the 1% level and indicates a slightly larger cyclone impact of −3.41 pp, which is 17% higher in absolute terms than the baseline estimate. Furthermore, the estimates derived from a regression based on the sample of individuals who relocated between two adjacent survey waves ("movers"—about 16% of the original sample) indicate a more pronounced negative effect (Panel A, Column 8). Specifically, the estimate for the cyclone impact is -4.69 pp, which is also statistically significant at the 5% level and 61% greater than the baseline estimate. The more pronounced effect for movers suggests a potential compounding impact of cyclone exposure and migration in reducing fertility.

We next evaluate the robustness of our core results through a series of model specifications and estimation techniques to ascertain whether our conclusions are contingent upon specific modelling choices or potential biases. We first refine the baseline individual FE regression by

excluding postcode dummy variables from the baseline regression (Panel A, Column 9). Second, we cluster standard errors at the individual level (Panel A, Column 10) to account for potential spatial correlation within individuals. These robustness checks are motivated by our research design, as discussed in Section 4. While treatment is measured at the postcode level, individuals residing within the same postcode may have differing exposure to the same cyclone during a given survey year due to variations in their interview timing. The results from these experiments remain largely consistent with the baseline estimate. Notably, excluding postcode fixed effects yields slightly more pronounced effects, with an absolute magnitude approximately 4% greater than the baseline estimate. Furthermore, clustering standard errors at the individual level does not affect the magnitude of the coefficient estimate, as expected, but results in a slightly smaller standard error compared to the baseline model. Importantly, the coefficient estimate retains its statistical significance at the 1% level.

Subsequently, we assess the sensitivity of our findings to time-invariant unobserved individual characteristics. Two models are considered: a pooled OLS regression, which does not control for time-invariant unobservable factors (Panel A, Column 11), and a Random Effects (RE) model, which assumes that individual-specific effects are uncorrelated with the independent variables (Panel A, Column 12). The estimates from these two specifications—both statistically significant at the 1% level—are approximately 8% larger in absolute terms than the baseline estimate. This notable increase in magnitude suggests that omitting time-invariant unobservable factors may lead to an overestimation of the diminishing effect of cyclones on fertility. These results, together with unreported Hausman test findings indicating strong within-individual correlation, underscore the suitability of the individual fixed effects model for this analysis.[21]

[21] In all pooled regressions, which do not account for unobservable individual time-invariant factors, time-invariant control variables such as gender and migration status were included to mitigate potential confounding

We next apply a RE logit model to account for the binary nature of the fertility outcome.[22] The results (Panel B, Column 1) indicate a more pronounced effect: exposure to a category 5 cyclone within 100 km of one's residence is associated with a 3.80 pp reduction in the probability of having a newborn child—approximately 30% larger in absolute terms than the baseline estimate. This amplified estimate is consistent with expectations, as linear probability models tend to underestimate effects when the mean of the binary dependent variable is close to zero or one—as is the case here, with a fertility mean of 0.06 (Wooldridge 2010). These findings suggest that our LPM estimates may represent a more conservative estimate of the diminishing impact of cyclone exposure on fertility.

To further evaluate the robustness of our findings, we exclude certain time-variant covariates from the baseline model. These covariates, including education and urban residency (Panel B, Column 2), may be endogenously influenced by cyclone events. Additionally, we perform robustness checks by separately controlling for several other time-variant variables that could be simultaneously affected by cyclones (Panel B, Columns 3–10). These variables include marital status; number of existing children (excluding the newborn child, if any); number of existing sons and number of existing daughters; equivalised household disposable income; individual regular market income; irregular non-wage income; Australian Government non-income support payments; and overall life satisfaction (See Appendix Table A1 for variable descriptions). Across these nine specification checks, our core finding—a statistically significant negative association between cyclone exposure and fertility—remains robust.

effects. Notably, the standard errors from the two pooled OLS regressions are significantly smaller than those from the baseline regression, further underscoring the suitability of the individual FE model (Wooldridge 2010).

[22] The FE logit model did not converge, likely due to the high dimensionality introduced by the large sample size and the inclusion of numerous dummy variables. Similarly, the RE logit model that incorporates postcode fixed effects also failed to converge. As a result, we perform a robustness check using an RE logit model without postcode fixed effects. Furthermore, to ensure comparability with the baseline linear probability model estimates, we report the results as average marginal effects (ME) derived from the logit regressions.

While controlling for each of the above variables individually does not materially alter the magnitude of the cyclone estimate, notable changes emerge with the inclusion of three variables (or sets of variables). First, including the marital status categorical variable reduces the estimated cyclone impact by 8% relative to the baseline (Panel B, Column 3).[23] Similarly, additionally controlling for overall life satisfaction reduces the cyclone estimate by 3% (Panel B, Column 10). In contrast, controlling for the number of existing children (Panel B, Column 4) or, alternatively, for the number of existing sons and daughters (Panel B, Column 5) increases the absolute magnitude of the cyclone estimate by approximately 15%.[24] As noted in Section 4, we deliberately omit the number of existing children as a control in the baseline regression, since this variable may be directly affected by cyclones. This is consistent with evidence of the devastating impact of cyclones on mortality globally (Huang *et al.* 2023; Young & Hsiang 2024) and with similar evidence presented in Section 8 of this study. These robustness results suggest that our baseline estimate is likely more conservative than estimates obtained when controlling for the number of existing children.[25]

Furthermore, we assess the robustness of our primary findings by employing two alternative measures of fertility. The first measure is binary, taking a value of one if an individual self-reported having given birth or adopted a child in the 12 months prior to the survey, and zero

[23] Unreported results indicate that estimates for being married or separated—relative to never being married (the reference category)—are statistically significant at the 1% level and positive, suggesting, as expected, that marriage, particularly current marriage, is associated with a higher likelihood of having children.

[24] The R-squared values, reported near the bottom of each panel and column, increase substantially with the inclusion of the number of existing children, highlighting the significant role of this variable in explaining fertility decisions, as documented in prior literature (Bloom *et al.* 2024). Unreported estimates for the number of existing children are negative and statistically significant at the 1% level, indicating that individuals with children are less likely to have a newborn child in our sample. Similarly, the coefficients for the number of existing sons and the number of existing daughters are comparable in magnitude, providing little evidence of gender-specific effects of existing children on the likelihood of having a newborn child.

[25] We also conducted robustness checks by separately including the one-year lagged values of two variables capturing fertility desires and intentions (see Appendix Table A1 for variable descriptions). Unreported results, available upon request, indicate that, as expected, individuals who previously expressed a stronger desire or intention to have more children are more likely to have a newborn child in the current survey wave. Moreover, consistent with the findings for the number of existing children, additionally controlling for these variables yields an even more pronounced cyclone effect on fertility. As discussed in Section 4, we intentionally exclude these variables from the baseline regression since they may be directly affected by cyclones. Furthermore, these variables have considerable missing data, and including their lagged values substantially reduces the sample size.

otherwise.[26] The results, presented in Panel B, Column 11 of Table 3, indicate that exposure to any category 5 cyclone within 100 km of its eye during the past 12 months significantly reduces the probability of having a birth or adoption by 4.24 pp, with statistical significance at the 1% level. This effect is substantial, representing approximately 72% of the sample mean fertility rate of 5.91% based on this self-reported measure.

The second alternative fertility measure is the number of living children, calculated as the difference between the total number of children an individual has ever had and the number of deceased children, measured annually at the time of the interview. Column 12 of Table 3 presents the results, revealing a statistically significant ($p < 0.01$) negative association between exposure to category 5 cyclones and the number of living children. Specifically, individuals exposed to a category 5 cyclone within 100 km of their residence in the past 12 months are estimated to have 0.06 fewer living children.[27] This estimate is substantial, accounting for 5% of the sample mean of 1.22 living children.

6.4. Impact by distance to the cyclone's eye

To additionally assess the robustness of our findings, we examine the differential impacts of cyclones based on their proximity to the cyclone's eye, utilizing three distance thresholds: 30 km, 100 km, and 200 km.[28] Consistent with prior analyses, our focus remains on exposure to category 5 cyclones, as this category is the only one demonstrated to have a statistically significant impact on fertility outcomes. The results, presented in Table 4, show that the

[26] This information is provided in the Self-Completed Questionnaire (SCQ) based on responses to a survey question asking, "Did any of these events occur to you in the past 12 months?" specifically prompting "Partner or I gave birth to, or adopted, a new child" (Summerfield *et al.* 2024). This data is available from Wave 2 onwards.
[27] We also examined the effects of incorporating both current and one-year lagged measures of exposure to category 5 cyclones and found statistically significant (at the 1% level) negative associations for both variables with the number of living children. The cumulative impact of current and one-year lagged exposure to category 5 cyclones is estimated at -0.11.
[28] Notably, the number of individuals exposed to a category 5 cyclone within a 30 km radius is relatively small, comprising only 360 person-year observations. This limited sample size likely contributes to the lack of strong statistical significance in the corresponding estimate. Accordingly, caution should be exercised when interpreting the results based on this measure of cyclone exposure.

estimated effects of cyclones on fertility decline substantially in absolute magnitude as the distance from the cyclone's eye increases.

Specifically, the impact of cyclone exposure on fertility decreases by 22% in absolute terms, from -3.75 pp to -2.92 pp, when comparing individuals residing within 30 km of the cyclone's eye to those located within 100 km. Similarly, in absolute terms, the effect decreases by 62%, from -2.92 pp to -1.10 pp, and its statistical significance diminishes—shifting from the 1% level to statistical insignificance—when comparing individuals within 100 km to those within 200 km. These findings underscore the critical role of geographical proximity in shaping individual responses to severe natural disasters.

6.5. Randomization tests

To further ensure the robustness of our results against potential model mis-specifications, we implement three variations of a randomization exercise, following the methodology of Hsiang and Jina (2014). The first approach, termed "whole sample", involves randomly assigning cyclone exposure observations across the entire sample. The second approach, labelled "between individuals", reallocates each individual's cyclone exposure history to another individual while preserving the timing of cyclone exposure. This method retains the chronological sequence of years and tests whether regional trends might generate spurious correlations. The third approach, called "within individual", randomly reassigns the timing of cyclone exposure within each individual, altering only the temporal structure of the data to investigate whether time-invariant cross-sectional patterns across individuals could produce false correlations.

We employ a modified version of Equation (1) that excludes postcode fixed effects[29] and uses a single dummy variable capturing concurrent exposure to any category 5 cyclone within a 100

[29] We exclude postcode fixed effects from this experiment to keep the computation time manageable, as their inclusion substantially increases processing time but does not materially change the results (see Section 6.3).

km radius of its eye as the exposure measure, which has previously been shown to significantly reduce fertility. Figure 1, which reports the results from these randomization tests, highlights two key findings. First, the distribution of false treatment effects is centred around a mean of zero, indicating that the model specified in Equation (1) is unlikely to produce biased estimates. Second, the coefficients derived from the actual data—represented by the solid red line and statistically significant at the 1% level—consistently lie in the left tail of the distribution, with p-values (the probability that the real-data estimate is smaller than or equal to the randomized estimates) less than or equal to 0.001 in all cases. These results strengthen the validity of our findings, indicating that the observed effects are highly unlikely to have occurred by chance.[30]

Overall, the analyses presented in this section demonstrate the robustness of our core findings across various sampling and methodological tests, including three randomization examinations. This comprehensive approach strengthens the validity of our baseline model and enhances confidence that the estimated effects accurately capture the causal impact of cyclones on fertility.

7. Heterogeneous cyclone impacts on fertility

Building on prior research on the likely mechanisms linking natural disasters to fertility and the identification of vulnerable populations (Lee *et al.* 2023; Bloom *et al.* 2024), we explore potential heterogeneity in the effects of cyclones across various sub-populations. We estimate these effects by applying Equation (1) separately to each of two distinct groups, defined by

[30] We also conduct similar randomisation tests using the continuous maximum wind speed of cyclones within 100 km of their eye as the exposure measure, with results reported in Appendix Figure A5. This figure shows that the distribution of placebo treatment effects is centred around a mean of zero. Moreover, the probability that the estimate from the actual data—statistically significant at the 10% level—is less than or equal to the estimates from the randomized data is below 0.0001 in all cases. By contrast, randomisation tests using exposure to Category 1–4 cyclones—excluding individuals affected by any Category 5 cyclones—are reported in Appendix Figure A6. These results indicate that the estimates from the actual data are not statistically significant, with placebo treatment effects centred around zero (all p-values > 0.10). This evidence further reinforces our earlier finding of no statistically significant effect of exposure to Category 1–4 cyclones on fertility.

eight individual and household characteristics.[31] These characteristics were selected based on prior studies suggesting that the differential impact and coping strategies related to natural disasters depend on preexisting financial resources (Hsiang & Narita 2012; Dell *et al.* 2014; Botzen *et al.* 2019; Ferreira 2024).

The individual characteristics include gender (male vs. female), age group (young vs. old, categorized relative to the median age of the baseline sample), education level ("lower" vs. "higher", with "lower" encompassing individuals with a Year 12 qualification or lower), marital status ("unmarried" vs. "married", with "married" including individuals who are married or in a de facto relationship), family size ("no child" vs. "any child"), and private health insurance status (insured vs. uninsured).[32] Household attributes encompass homeownership status (renters vs. homeowners), income group (lower vs. higher income, defined relative to the median of the real equivalised household income), and residential insurance status (insured vs. uninsured).[33]

To address potential concerns regarding how cyclones may influence behaviours such as migration or insurance acquisition (Nguyen & Mitrou 2024b, 2025d), which could subsequently affect sub-population classification, individuals are categorized based on time-variant characteristics (excluding age) observed at their initial inclusion in the sample. Consistent with the baseline analysis, this subsection uses a cyclone exposure indicator that

[31] We do not conduct a heterogeneity analysis based on other characteristics due to the absence of a strong theoretical or empirical rationale, as well as limited statistical power stemming from small sample sizes or a low number of affected individuals.

[32] Private health insurance status is derived from responses to the question, "Were you covered by private patient hospital cover for the entire previous financial year?" and is available only from Wave 12 onwards (Summerfield *et al.* 2024).

[33] Building on the classification employed by Nguyen and Mitrou (2024b, 2025d), this study categorizes individuals as "insured" if their reported annual household expenditure on combined home, contents, and motor vehicle insurance exceeds $1,250 (adjusted to 2010 prices). Those reporting lower expenditures are classified as "uninsured". Data on home and contents insurance is obtained from Wave 6 onwards, based on responses to the "other insurance (home/contents/motor vehicle)" expenditure question (Summerfield *et al.* 2024).

reflects whether individuals were exposed to any category 5 cyclone within a 100 km radius of its eye in the 12 months preceding the survey date.

Figure 2 presents a graphical representation of the regression estimates for the impact of category 5 cyclone exposure on fertility, alongside the sample mean of the fertility measure, stratified by various population subgroups. The results suggest a more pronounced effect for selected subgroups, as indicated by more negative and statistically significant estimates. For example, subgroup estimates reveal a stronger effect of cyclone exposure on the fertility of younger individuals, who have nearly double the fertility rate of their older counterparts (7.25% compared to 3.81%). The estimated impact for this subgroup is over 15 times greater in absolute magnitude (-4.77 pp compared to -0.31 pp for older individuals) and is statistically significant ($p < 0.01$) exclusively for younger individuals.

Similarly, subgroup estimates based on education reveal notable disparities in both baseline fertility and responses to cyclone exposure between individuals with lower and higher education levels. Consistent with recent trends in high-income countries (Bloom *et al.* 2024), our data indicate a higher mean fertility rate among higher-educated individuals (6.39%) compared to their lower-educated counterparts (5.05%). However, cyclone exposure has a more pronounced impact on the fertility of lower-educated individuals, with an estimated effect approximately 15% greater in absolute magnitude than that observed for higher-educated individuals (-2.74 vs. -2.38 pp, respectively). Notably, this effect is statistically significant at the 1% level exclusively for the lower-educated subgroup.

As anticipated, subgroup analyses based on initial family size are consistent with earlier findings by age group, as younger individuals typically have smaller family sizes. These analyses also reveal a more pronounced impact among individuals who did not have a child at the beginning of the study period—a pattern consistent with that reported by Fontaine *et al.* (2024), who focus on six developing countries and find that the decline in births was smaller

among mothers who already had children. Specifically, compared to those with at least one child at the outset, individuals without children exhibit higher baseline fertility (6.02% vs. 4.81%, respectively). Moreover, the estimated impact of cyclone exposure is more than four times greater for individuals without a child at the start of the study period (-3.82 pp compared to -0.80 pp), with statistical significance at the 1% level observed exclusively for this group.

Additionally, subgroup estimates based on previous home insurance status reveal a more pronounced impact for uninsured individuals. The estimated effect for this group is over three times greater in absolute magnitude (-4.56 pp compared to -1.25 pp for insured individuals) and is statistically significant ($p < 0.01$) exclusively for uninsured individuals. Furthermore, the estimated reduction in fertility for uninsured individuals is substantial, representing 74% of their baseline mean of 6.19% for uninsured individuals having any newborn child in a given year. Similarly, subgroup estimates by prior private health insurance status show a stronger impact for uninsured individuals. The estimated effect for this group is about 1.8 times larger in absolute magnitude (-3.85 pp compared to -2.14 pp for insured individuals) and is statistically significant ($p < 0.01$) exclusively for the uninsured.

The strong consistency in the heterogeneous impacts of cyclones by residential and private health insurance status is expected, given that in Australia's universal public health system, individuals with residential insurance are much more likely to hold private health insurance. Moreover, many factors influence decisions regarding both types of insurance in similar ways (Nguyen *et al.* 2023; Nguyen & Mitrou 2024b).

These differential impacts of cyclones on fertility may stem from preexisting disparities between insured and uninsured populations. Prior home and contents insurance may alleviate the financial burden of cyclone-induced damage, thereby reducing the need for relocation, as shown in Nguyen and Mitrou (2024b). Similarly, private health insurance can mitigate health-related costs associated with natural disasters, consistent with prior evidence showing a positive

association between private health insurance and subsequent healthcare utilization, particularly for services not covered by the public system (Nguyen *et al.* 2024a; Nguyen & Mitrou 2025d). Consequently, the absence of a statistically significant fertility effect among individuals with prior residential or private health insurance likely reflects the mitigating role of insurance coverage. To our knowledge, this finding highlights a novel role for residential and health insurance in buffering the adverse effects of natural disasters on fertility—an area that remains underexplored in the existing literature (Kousky 2019; Carleton *et al.* 2022).

Figure 2 also indicates no substantial differences in the estimated effects of cyclone exposure across other examined characteristics, including gender, marital status, home ownership, and household income. While the estimates for these subgroups are statistically significant at the 10% level or better, they tend to be of similar magnitude, suggesting relatively uniform responses across these dimensions. Overall, the subgroup analyses highlight considerable heterogeneity in the fertility response to category 5 cyclone exposure.[34] Individuals with specific characteristics—including younger age, lower educational attainment, no children at baseline, and lack of prior residential or health insurance—experience more pronounced reductions in fertility following exposure to a severe cyclone.[35]

Above, we found that cyclone effects are concentrated among certain subsets of the population, particularly younger individuals. An important open question is whether these more affected individuals compensate for the early reduction in fertility by having more children later in life.

[34] Appendix Figure A7 displays the results of a heterogeneity analysis examining exposure to remaining category 1 to 4 cyclones within 100 km of their eye. Consistent with the statistically insignificant effect estimated for the full sample, represented by the dashed horizontal line, the subgroup estimates also lack statistical significance. This absence of significant effects across these cyclone categories reinforces our conclusion regarding the highly non-linear relationship between cyclone intensity and fertility outcomes.

[35] This conclusion is primarily based on the statistical significance of one subgroup and the lack of significance in the other. Since Stata does not readily provide a formal test for differences in coefficient estimates across separate FE regressions, we employed an informal approach: visually inspecting whether the 95% confidence intervals of the two estimates overlap. This inspection indicates 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 with relatively small sample sizes or when only one subgroup's estimate is statistically significant (Wooldridge 2010).

To investigate this potential longer-term impact—analogous to the baseline analysis for the full population—we estimate a dynamic regression model similar to Equation (1), incorporating two-year lagged exposure to a Category 5 cyclone within 100 km of its eye, alongside the current exposure measure. This modified model is applied separately to each subgroup, defined by the socio-demographic characteristics described above.

Appendix Table A6 reports the results of this analysis and suggests no evidence of delayed fertility following cyclone exposure, as neither the one-year nor two-year lagged exposure variables are statistically significant at conventional levels in any subgroup regression. By contrast, the estimates for current cyclone exposure remain highly statistically significant and negative, and—consistent with earlier heterogeneous analysis—are more pronounced among younger individuals, those with lower education, childless individuals at baseline, and members of uninsured households.

The consistency of these results is notable given the substantial reduction in sample size caused by the inclusion of lagged cyclone exposure variables, reinforcing the robustness of our finding that the fertility impact of cyclones is short-lived. Taken together with the whole-population estimates, these subgroup results suggest that the fertility loss attributable to the most severe Category 5 cyclones is permanent. To our knowledge, this is a novel finding in the literature, made possible by our use of unique long-term individual panel data and dynamic empirical models. The result is particularly important as it indicates that severe cyclones may lead to a permanent reduction in total population, through both a decrease in births—as shown here—and the increase in mortality documented in the international literature (Huang *et al.* 2023; Young & Hsiang 2024). Moreover, our finding of a substantial decline in fertility following these most severe cyclones, when considered alongside prior evidence of higher infant mortality rates—and greater mortality risks for infants compared to other age groups—after tropical cyclones (Anttila-Hughes & Hsiang 2013; Young & Hsiang 2024), suggests that

mortality rate estimates may be biased downwards unless these fertility changes are explicitly incorporated.

8. Discussion of main findings and potential mechanisms

8.1. Discussion of main findings

The findings presented above provide robust evidence that exposure to a category 5 cyclone—the most severe classification—results in a highly statistically significant reduction in fertility. The most pronounced effect is observed for individuals exposed to a category 5 cyclone within 30 km of its eye during the 12 months preceding the survey, with an estimated decrease in the probability of having a newborn child of 3.75 pp. This corresponds to a 67% reduction relative to the sample mean. This micro-level evidence of a negative impact of cyclones on the fertility of Australians aligns with macro-level evidence of the negative impact of the 2011 East Japan Earthquake and the subsequent Fukushima Daiichi Nuclear Power Plant disaster on the fertility of Japanese (Hamamatsu *et al.* 2014; Kurita 2019; Körblein 2021). The Australian evidence is also consistent with macro-level evidence of a reduction in birth rates following the 1997 Red River flood in North Dakota, USA (Tong *et al.* 2011). Interestingly, the evidence from this study, which focuses on a developed country such as Australia, is consistent with the findings of Fontaine *et al.* (2024), who employ a similar empirical approach to analyse six developing countries. However, our findings do not align with county-level evidence of an increase in birth rates in the year following Hurricane Hugo in 1989 in the USA (Cohan & Cole 2002).

Our finding of a statistically significant negative impact on fertility associated with the most severe category 5 cyclones is also consistent with macro-level evidence that high-severity storm advisories have a significant negative impact on fertility in a US study by Evans *et al.* (2010). However, unlike Evans *et al.* (2010), who found that low-severity storm advisories are associated with a statistically significant positive fertility effect, our study presents a

statistically insignificant impact of less severe cyclones (i.e., category 4 or lower) on the fertility of Australians.

While our results may not fully reconcile the mixed findings in the current literature—which is understandable given substantial differences across previous studies in study contexts, types of natural disasters, measures of disaster exposure, and empirical models—our findings suggest some potential sources of these discrepancies. For example, our comprehensive sensitivity checks, which support the robustness of our main findings, indicate that estimates may vary depending on the selected samples, measures of cyclone exposure, fertility outcomes, and empirical models.

Moreover, our heterogeneous analyses reveal that the fertility of certain groups is more negatively affected by cyclones than others, suggesting that differences in study contexts and sample compositions may explain variations in international findings. This is consistent with a U.S. study by Seltzer and Nobles (2017), who found that following Hurricane Katrina in 2005, fertility rates of Black individuals in New Orleans decreased relative to other unaffected cities, whereas fertility among White individuals increased. Together, these heterogeneous results—despite notable differences in data and empirical models across studies—suggest that the effects of cyclones may vary across specific population subgroups.

These divergences, both within and across studies, indicate that the impacts of cyclones on fertility are likely context-specific and should not be generalized across countries or types of natural disasters. Further research is therefore needed to assess whether similar patterns hold in other settings, using robust models that account for individual fixed effects and exogenously measured disaster exposures, as employed in this study whenever possible.

Direct comparisons of the magnitude of our estimated cyclone impacts on fertility with findings from other studies on the effects of different factors are challenging due to potential

discrepancies in fertility measures, empirical models, and study contexts.[36] To contextualize the relative magnitude of our estimates, we draw on evidence from countries with comparable levels of development. For instance, Del Bono *et al.* (2012) report that job displacement due to firm closures in Austria led to a reduction in long-run fertility rates among women by 2.0 to 5.9 pp, corresponding to a 3.2% to 9.5% decline relative to the mean fertility rate. Similarly, González and Trommlerová (2023) document that the removal of a universal child benefit in Spain resulted in a 6% decrease in birth rates. As noted above, our largest estimated reduction in fertility—specifically, a 3.75 pp decline associated with exposure to a category 5 cyclone within 30 km of the home, equivalent to a 67% reduction relative to the sample mean—is comparable to, or even larger than, the documented effects of job displacement in Austria and the elimination of child benefits in Spain.

8.2. Potential mechanisms

Existing literature postulates various mechanisms through which natural disasters might influence fertility decisions, including mortality, resource scarcity, infrastructure damage, displacement, partnership dynamics, and psychological stress (Becker & Barro 1988; Doepke *et al.* 2023; Lee *et al.* 2023). This section aims to explore potential pathways linking cyclone exposure to reduced fertility.

To do so, we estimate an individual FE model similar to Equation (1), introducing as separate dependent variables a range of factors that may be affected by cyclone exposure and are plausibly linked to childbearing decisions. We introduce two indicator variables describing whether the individual resided in a postcode affected by any category 5 cyclone within 100 km from its eye in the current or previous year relative to the survey time. Moreover, the same sample restrictions apply to ensure the results are comparable to the previously documented

[36] We similarly refrain from directly comparing the magnitude of our estimated cyclone impacts on fertility with reported effects of natural disasters on fertility in studies using data from the US and Japan.

cyclone impacts on fertility. Estimates of these cyclone exposure indicators from these models can be interpreted as the direct effects of cyclones on the specific outcome (Nguyen & Mitrou 2024b, 2025d). These factors may have concurrent or lagged associations with fertility decisions (Doepke *et al.* 2023; Lee *et al.* 2023), and the estimated coefficients provide insights into the potential mechanisms through which cyclones might influence fertility.

The rich and detailed information within the HILDA data makes it particularly valuable for this analysis. It allows us to simultaneously explore many of these potential channels, most of which lack formal validation in the literature due to data limitations or the absence of robust empirical models (Lee *et al.* 2023). Specifically, to explore the potential mortality and physical health channel, we draw on variables such as serious personal illness, general health status, serious injury/illness to family member, and any child deceased since the last survey (Nguyen & Mitrou 2025d).[37] To proxy resource scarcity and infrastructure damage, we use measures including equivalised household disposable income, individual regular market income, non-wage irregular income, Australian Government non-income support payments, and whether the individual's home was damaged or destroyed by a natural disaster (Nguyen & Mitrou 2024b). We consider residential relocation to explore the displacement and disruption channels (Nguyen & Mitrou 2024b). Additionally, we incorporate various factors capturing family dynamics and reproductive behaviours, including marital status, fertility desires and intentions (Doepke & Kindermann 2019; Corno *et al.* 2020), and pregnancy status (Goldin & Katz 2002; Bailey 2006).[38]

[37] Appendix Table A1 provides descriptions and summary statistics for these variables. All monetary variables are measured by financial year, expressed in thousands of dollars, and adjusted for inflation using the Consumer Price Index (CPI), with 2010 as the base year.

[38] "Fertility desires" are constructed from responses to the question, "Would you like to have [a child of your own/more children] in the future?", with responses ranging from 0 ("Definitely does not want children") to 10 ("Very much like to have children"). "Fertility intentions" are derived from responses to the question, "How likely are you to have [a child/more children] in the future?", with responses ranging from 0 ("Very unlikely") to 10 ("Very likely"). These questions are asked of individuals aged under 55 and are available in all survey waves. Data collection on major life events began in Wave 2, while information on weather-related home damage is only available from Wave 9 onwards. It should be noted that the unavailability of certain variables in selected waves

Moreover, following previous Australian studies (Nguyen & Mitrou 2024a, 2025d), we employ overall life satisfaction and satisfaction specific to personal safety and health to capture potential psychological stress.[39] For similar reasons, we also consider two insurance-related variables: (i) a dummy variable indicating whether the individual resides in a household with residential insurance coverage, as defined previously in Section 7 and consistent with the classification in Nguyen and Mitrou (2024b); and (ii) a binary variable indicating whether the individual reported having private patient hospital cover, as defined in Section 7 and in line with Nguyen and Mitrou (2025d). These variables are included because prior studies suggest that natural disasters may increase insurance uptake as a coping strategy in response to heightened perceptions of property and health risks (Kousky 2019; Nguyen & Mitrou 2024b, 2025d). In addition, heightened risk perceptions may influence both insurance uptake and fertility decisions (Doepke *et al.* 2023; Lee *et al.* 2023).

The results from this analysis, presented in Table 5, suggest that the physical health of individuals or their family members is unlikely to be a channel through which cyclone exposure reduces fertility. This conclusion is based on the fact that the estimates for all variables capturing physical health-related factors—such as experience of serious personal illness, individual general health, and serious injury/illness to family member (reported in Panel A, Columns 1 to 3)—are not statistically significant at any conventional level.

However, the estimates for child mortality suggest that it is a likely channel through which cyclone exposure reduces fertility.[40] This is evidenced by a statistically significant positive

results in a significantly reduced sample size for some regressions. Therefore, caution should be exercised when interpreting these results.

[39] "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 ranging from 0 ("Completely dissatisfied") to 10 ("Completely satisfied"), with higher scores indicating greater life satisfaction. Satisfaction with personal safety and health is constructed from responses to questions asking respondents about their satisfaction with how safe they feel and their health, respectively. These life satisfaction variables are available in all survey waves.

[40] It is important to emphasize that the estimated association between cyclone exposure and child mortality should not be interpreted as the causal impact of cyclones on child mortality. This is because our measure of child mortality—defined as a binary variable equal to 1 if the respondent has any deceased child at the time of the

estimate (at the 5% level) for exposure to concurrent cyclones and a statistically significant positive estimate (at the 10% level) for exposure to one-year lagged cyclones on the probability of having any deceased children (Panel A, Column 4). These positive estimates indicate that cyclones may have contributed to child mortality, consistent with international literature highlighting the substantial impact of cyclones on mortality globally (Anttila-Hughes & Hsiang 2013; Huang *et al.* 2023; Young & Hsiang 2024).

The statistically insignificant estimates of both concurrent and lagged cyclone exposure indicators on all income-related variables (reported in Panel A, Columns 5 to 8, consistent with Nguyen and Mitrou (2025d)) suggest that financial factors are unlikely to serve as a channel through which cyclone exposure reduces fertility for individuals in this study. Furthermore, residential relocation does not appear to account for the impact of cyclone exposure on reduced fertility among Australians of reproductive age, as evidenced by the statistically insignificant cyclone estimates for this variable (Panel A, Column 10).

The estimate of concurrent cyclone exposure on weather-related home damage, reported in Panel A, Column 9, is positive and highly statistically significant at the 5% level, suggesting that individuals affected by cyclones are more likely to report home damage.[41] This result, which confirms a similar finding by Nguyen and Mitrou (2024b), when considered alongside the observed reducing impact of weather-related home damage on individuals' psychological well-being and positive personality traits (Nguyen & Mitrou 2024a, 2025b, a, c), suggests that weather-related home damage is likely a pathway through which cyclone exposure diminishes fertility in this study.

survey, and 0 otherwise—does not indicate whether the deceased child was living with the respondent at the time of cyclone exposure. Consequently, the death may not be directly attributable to the cyclone.

[41] The estimate for lagged cyclone exposure on home damage is notably negative and statistically significant at the 1% level. This finding is consistent with the results from an Australian study by Nguyen and Mitrou (2024b), who attribute the reduced home damage reported by individuals who experienced a cyclone in the previous year to their proactive acquisition of residential insurance in response to the initial event. This proactive measure helps mitigate the effects of subsequent cyclones, leading to lower reported damage in the follow-up period.

Likewise, the statistically significant, albeit at the 10% level, negative estimates for both concurrent and one-year lagged cyclone exposure on the probability of marriage (Panel B, Column 1) suggest that individuals are less likely to marry up to two years following exposure to a category 5 cyclone. Similarly, the highly statistically significant (at the 1% level, as shown in Panel B, Column 2) positive estimate for the lagged cyclone exposure variable on the separation status variable indicates that cyclone-affected individuals are significantly more likely to experience separation, divorce, or widowhood.[42] These results suggest that reduced family formation, driven by lower marriage rates, coupled with increased family disintegration due to higher divorce and separation rates, may serve as potential mechanisms through which cyclone exposure reduces fertility. This finding aligns with the well-established pattern that married individuals tend to have more children (Bloom *et al.* 2024), a pattern that is also confirmed in our previous heterogeneity analysis.

Similarly, the statistically significant negative estimates of cyclone exposure on overall life satisfaction and two satisfaction domains related to personal safety and health (Panel B, Columns 6-8) suggest that psychological stress may be another potential mechanism. Specifically, in line with the findings of Nguyen and Mitrou (2024a), cyclone exposure has a statistically significant negative concurrent impact on these three well-being outcomes, as well as a delayed impact on personal safety satisfaction. The statistically significant negative effect of cyclone exposure on these psychological outcomes, when considered alongside the statistically insignificant effects of cyclone exposure on fertility desires or intentions (reported in Panel B, Columns 3 and), the slight decrease in pregnancy following cyclone exposure in the previous year (Panel B, Column 5, providing further evidence of cyclones' impact on overall fertility), and the established link between stress and infertility (Rooney & Domar

[42] This finding is consistent with the evidence presented by Deryugina *et al.* (2018), who similarly observe that individuals affected by Hurricane Katrina in the U.S. are more likely to experience divorce following the disaster.

2018), collectively suggest that psychological stress may be a significant contributing factor to the reduced fertility observed following cyclone exposure.

In a similar vein, the positive and statistically significant estimate of concurrent cyclone exposure on residential insurance (Panel B, Column 9), as well as the positive and statistically significant estimates of concurrent and one-year lagged cyclone exposures on health insurance enrolment (Panel B, Column 10), suggest that, consistent with prior Australian evidence (Nguyen & Mitrou 2024b, 2025d), individuals exposed to these severe Category 5 cyclones are more likely to increase insurance coverage. This behaviour likely reflects efforts to mitigate potential damages from future natural disasters and indicates elevated risk perceptions, which may in turn reduce current fertility (Doepke *et al.* 2023; Lee *et al.* 2023).

Overall, the results in this section suggest that physical health, financial factors, and migration are unlikely to be the primary channels through which cyclone exposure reduces fertility in this study. Instead, reduced family formation, increased family disintegration, child mortality, cyclone-induced home damage, heightened psychological stress, and elevated risk perceptions emerge as likely pathways through which cyclone exposure diminishes fertility.

While this study provides suggestive evidence on potential mechanisms underlying the effect of cyclones on fertility, establishing causal relationships for these mechanisms remains challenging. A commonly used approach to identify the contribution of each of the above factors is to include them as explanatory variables or mediators in the fertility equation (see, for example, Celli (2022) for a review on causal mediation analysis in economics). However, doing so raises potential endogeneity concerns, as unobservable factors affecting fertility may also be correlated with these mediators.[43] To establish causality for these mechanisms, it is

[43] This consideration partially explains why these variables were not included in our baseline regressions (Angrist & Pischke 2009). Nevertheless, in several robustness checks presented in Section 6.3, we separately incorporated time-varying variables capturing potential mechanisms, such as marital status, income, and overall life satisfaction. The results indicate that including income variables does not materially affect the magnitude of the cyclone estimate, consistent with our earlier finding that income factors are unlikely to represent the primary

essential to address the endogeneity of the mediators, for instance, by identifying valid instruments for each and applying an instrumental variable approach (Frölich & Huber 2017; Celli 2022). Given the absence of a plausible strategy to resolve this endogeneity problem, causal mediation analysis is left for future research.

9. Conclusion

This study adopts a natural experiment design, leveraging the exogenous timing of local cyclone exposure, to provide the first causal analysis of their impact on fertility among Australians of reproductive age. The findings indicate a significant decline in fertility following exposure to the most severe category 5 cyclones, suggesting that this fertility loss is effectively permanent. The effect intensifies as the distance between the individual's residential postcode and the cyclone's eye decreases. The largest impact—a 3.75 percentage point reduction in the probability of having a newborn, equivalent to approximately 67% of the sample mean—is observed among individuals exposed to a category 5 cyclone within 30 km of its eye in the 12 months preceding the survey. The robustness of these findings is supported by a series of sensitivity checks, including a falsification test showing that future cyclones do not affect current fertility, and various randomization tests.

Extensive heterogeneity analyses reveal that the fertility decline following cyclone exposure is more pronounced among younger individuals, those with lower educational attainment, childless individuals at baseline, those without prior private health insurance, and residents of households lacking prior residential insurance. Additionally, the study provides suggestive evidence that reduced family formation, increased family dissolution, child mortality, cyclone-

channels through which cyclone exposure reduces fertility. By contrast, including marital status and overall life satisfaction as additional control variables reduces the absolute magnitude of the estimate by 8% and 3%, respectively. This reduction aligns with the results presented in this section, suggesting that reduced family formation, increased family disintegration, and heightened psychological stress are plausible pathways through which cyclones diminish fertility in this study. We refrain from including other potential factors as additional controls because they involve substantial missing information, which significantly reduces the sample size and renders the resulting cyclone estimate not directly comparable to the baseline.

induced home damage, heightened psychological stress, and elevated risk perceptions are plausible pathways through which cyclones reduce fertility. By contrast, individual physical health, financial constraints, and migration appear less likely to account for the observed association.

This study provides robust evidence on the impact of cyclone exposure on human fertility, contributing to a growing understanding of the demographic consequences of natural disasters. Nonetheless, several limitations warrant consideration and highlight avenues for future research. First, the data and identification strategy employed in this study do not allow for causal inference regarding the effects of other natural disasters, such as droughts or floods, on fertility outcomes. Further research leveraging alternative datasets or methodologies would be valuable for assessing the distinct impacts of different types of natural hazards. Second, while this study identifies plausible mechanisms through which cyclones may reduce fertility, it does not quantify the relative contribution of each pathway. Addressing this gap requires further theoretical development and empirical analysis to unpack the complex interrelationships underlying fertility responses to disaster-related stressors.

The findings presented in this study have important methodological and policy implications. Methodologically, the results underscore the value of employing individual-level panel data, where available, and using individual fixed effects models to estimate the effects of natural disasters on fertility. Failure to account for individual time-invariant unobserved factors may lead to an overestimation of the negative effect of cyclones on fertility by approximately 8%.

From a policy perspective, the robust evidence of a substantial negative impact of severe cyclones on fertility underscores the need for targeted interventions to support affected populations—particularly those who are disproportionately vulnerable. Specifically, our novel finding that these severe cyclones do not reduce the fertility of individuals with prior residential or health insurance highlights the mitigating role of insurance coverage. This suggests that

policies promoting broader uptake of such insurance could help lessen the adverse effects of natural disasters on fertility. Moreover, the finding that cyclone exposure has a more pronounced impact on the fertility of lower-educated individuals—who generally have fewer cognitive or financial resources to cope with natural disasters (Dell *et al.* 2014; Botzen *et al.* 2019)—indicates a need for targeted support for these disadvantaged groups to mitigate the fertility-reducing effects of cyclones.

In the same vein, our investigation into the potential mechanisms underlying the cyclone–fertility relationship provides further insights for policy design. For instance, our finding that Category 5 cyclones reduce family formation, increase family dissolution, cause home damage, and elevate psychological stress suggests that policies aimed at mitigating family breakdown, housing damage, and psychological distress may help alleviate the negative impacts of cyclones on fertility. Similarly, our finding that these severe cyclones increase insurance uptake—combined with the null effect of cyclones on the fertility of previously insured individuals—reinforces the importance of policies that promote broader insurance coverage as a means to buffer households against the adverse demographic consequences of natural disasters. Overall, these insights can inform the design of policies aimed at enhancing disaster resilience, mitigating long-term demographic consequences, and addressing the broader social and economic costs of extreme weather events.

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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)	33.208	33.267	-0.059
Male [(a)]	0.514	0.512	0.002
NESB migrant [(a)]	0.066	0.104	-0.038***
ESB migrant [(a)]	0.084	0.077	0.007*
Year 12 [(a)]	0.197	0.191	0.006
Vocational or training qualification [(a)]	0.389	0.353	0.035***
Bachelor or higher [(a)]	0.187	0.207	-0.020***
Major city [(a)]	0.344	0.632	-0.288***
Local area unemployment rate (%)	4.995	5.087	-0.092***
Local area SEIFA index	5.306	5.541	-0.235***
Number of alive children	1.236	1.215	0.022
Any newborn child [(a)]	0.051	0.056	-0.005
Observations	5,499	127,885	

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: Impacts of cyclone exposure on fertility

	(1)	(2)	(3)	(4)	(5)
Current category 1	-0.16	-0.25	-0.58	-0.37	
	[1.00]	[0.95]	[1.02]	[1.08]	
Current category 2	-0.32	0.46	-0.01	-0.13	
	[1.48]	[1.72]	[1.85]	[1.62]	
Current category 3	-1.38	-0.40	0.07	-1.84	
	[1.48]	[1.80]	[2.05]	[1.62]	
Current category 4	-0.41	-0.59	0.07	-0.77	
	[0.86]	[0.90]	[0.96]	[0.93]	
Current category 5	-3.04***	-3.37***	-2.94***	-3.29***	-2.92***
	[0.94]	[1.12]	[1.13]	[0.93]	[0.95]
One-year lagged category 1		0.27	0.45		
		[1.08]	[1.14]		
One-year lagged category 2		2.37	2.73		
		[1.67]	[1.81]		
One-year lagged category 3		0.76	2.11		
		[1.56]	[2.41]		
One-year lagged category 4		0.36	0.29		
		[0.91]	[0.92]		
One-year lagged category 5		-0.16	-0.27		
		[1.20]	[1.30]		
Two-year lagged category 1			0.57		
			[0.99]		
Two-year lagged category 2			-0.80		
			[2.17]		
Two-year lagged category 3			3.11		
			[2.26]		
Two-year lagged category 4			0.14		
			[0.99]		
Two-year lagged category 5			1.25		
			[1.74]		
One-year lead category 1				0.05	
				[0.93]	
One-year lead category 2				-1.40	
				[1.34]	
One-year lead category 3				-2.25	
				[1.90]	
One-year lead category 4				-1.00	
				[1.01]	
One-year lead category 5				0.69	
				[1.40]	
Observations	133,384	114,372	99,368	117,480	133,384
No of unique individuals	14,274	12,281	10,822	12,507	14,274
Overall R squared	0.17	0.17	0.17	0.17	0.17
Within R squared	0.01	0.01	0.01	0.01	0.01
Mean of dep. variable	5.60	5.70	5.76	5.74	5.60

Notes: Results reported in each column are from a separate individual FE regression, using Equation (1). 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, standard errors and sample means) are multiplied by 100 for aesthetic purposes. Dependent variable: Any newborn child. Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported 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)	(12)
Panel A:	Baseline	Sample: Individuals aged between 18 and 49 years	Sample: Individuals aged 15 or older	Sample: LGAs affected by any cyclone within 100 km	Sample: Whole Australia	Sample: Excluding individuals affected by cyclones of categories 1–4	Sample: Stayers	Sample: Movers	Excluding postcode dummies	Clustering at the individual level	Using a pooled cross-sectional model	Using a RE linear probability model
Category 5 cyclone exposure	-2.92***	-3.39***	-2.00***	-2.91***	-2.87***	-2.94***	-3.41***	-4.69**	-3.03***	-2.92***	-3.16***	-3.16***
	[0.95]	[1.10]	[0.64]	[0.97]	[0.92]	[1.01]	[1.30]	[2.28]	[0.86]	[0.76]	[0.86]	[0.86]
Observations	133,384	114,892	210,162	72,169	221,416	128,597	85,663	21,605	133,433	133,384	133,384	133,384
N of unique individuals	14,274	12,882	18,433	8,017	22,709	14,163	11,517	5,871	14,279	14,274	14,274	14,274
Overall R squared	0.17	0.17	0.18	0.17	0.16	0.17	0.21	0.36	0.15	0.17	0.06	0.19
Within R squared	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.02	0.01		0.03
Mean of dep. variable	5.60	6.44	3.57	5.57	5.40	5.61	5.10	7.58	5.60	5.60	5.60	5.60
Panel B:	Using a RE Logit model (ME)	Excluding variables such as education and urban residency	Including a variable: Marital status	Including a variable: Number of children	Including a variable: Number of sons and number of daughters	Including a variable: Equivalised household disposable income	Including a variable: Individual regular market income	Including a variable: Individual non-wage irregular income	Including a variable: Non-income support payments	Including a variable: Overall life satisfaction	Employing "any birth/adoption of new child" as an outcome	Employing "number of alive children" as an outcome
Category 5 cyclone exposure	-3.80***	-2.94***	-2.70***	-3.37***	-3.38***	-2.92***	-2.93***	-2.92***	-2.83***	-2.83***	-4.24***	-0.06***
	[1.11]	[0.95]	[0.96]	[0.98]	[0.99]	[0.95]	[0.95]	[0.95]	[0.94]	[0.95]	[0.96]	[0.02]
Observations	133,384	133,384	133,372	133,384	133,384	133,210	133,210	133,091	133,054	133,330	111,434	133,370
N of unique individuals	14,274	14,274	14,272	14,274	14,274	14,263	14,263	14,261	14,260	14,270	12,879	14,274
Overall R squared		0.17	0.18	0.22	0.22	0.17	0.17	0.17	0.17	0.17	0.19	0.92
Within R squared		0.01	0.03	0.07	0.07	0.02	0.01	0.01	0.02	0.02	0.02	0.11
Mean of dep. variable		5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.91	1.22

Notes: The results presented in each column and panel are based on a separate FE regression, unless otherwise specified. Dependent variable: Any newborn child, unless indicated otherwise. Cyclone exposure measure: Concurrent exposure to any category 5 cyclone within 100 km. For binary outcome variables, results (coefficient estimates, standard errors and sample means) are multiplied by 100 for aesthetic purposes. For Logit regressions, results (coefficient estimates and standard errors) are reported in marginal effects (ME). "Proportion affected" represents the share of individuals in the respective sample who were impacted by any category 5 cyclone in the previous year. Unless stated otherwise, other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level, unless indicated otherwise, are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Impacts of cyclones by distances to the cyclone's eye

Distance to cyclone eye:	≤30km	≤100km	≤200km
	(1)	(2)	(3)
Exposure to a category 5 cyclone	-3.75**	-2.92***	-1.10
	[1.56]	[0.95]	[0.81]
Observations	133,384	133,384	133,384
Number of unique individuals	14,274	14,274	14,274
Overall R squared	0.17	0.17	0.17
Within R squared	0.01	0.01	0.01
Mean of dependent variable	5.60	5.60	5.60
Proportion affected by any category 5 cyclone last year (%)	0.27	0.61	1.31

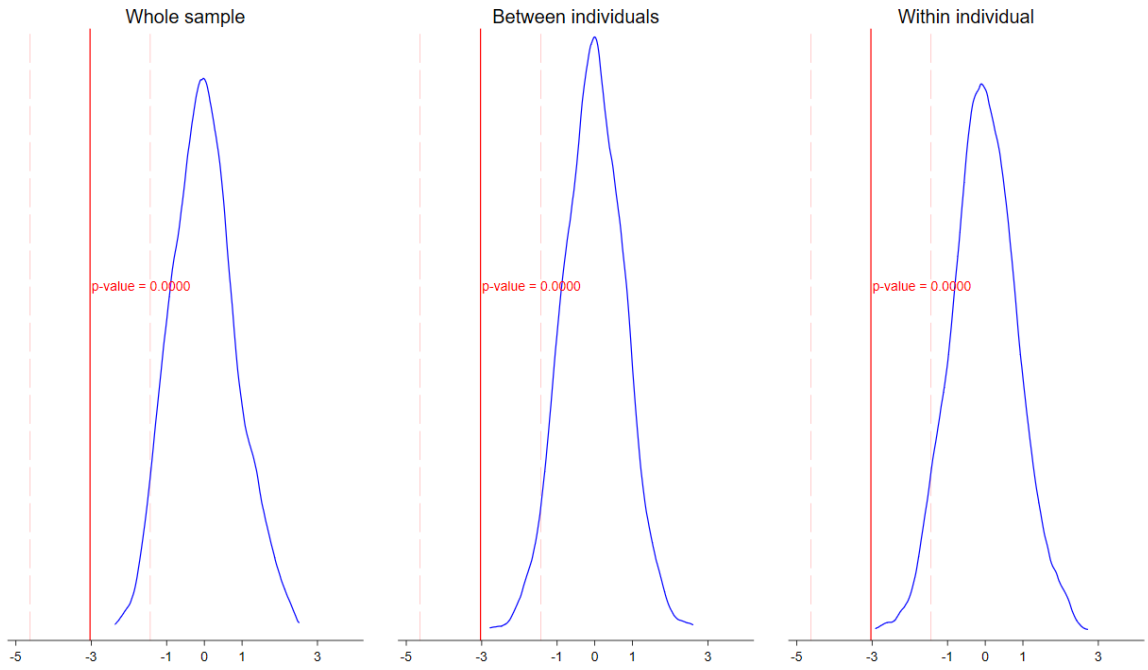
Notes: Results reported in each column are from a separate individual FE regression, using Equation (1). Results (coefficient estimates, standard errors, and sample means) are multiplied by 100 for aesthetic purposes. Dependent variable: Any newborn child. Cyclone exposure measure: Concurrent exposure to any category 5 cyclone within the distance threshold specified in the first row of this table. Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: Potential mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:	Experience of serious personal illness[(a)]	General health	Serious injury/illness to family member[(a)]	Any deceased child[(a)]	Equivalised household disposable income	Individual regular market income	Individual non-wage irregular income	Australian Government non-income support payments	Weather related home damage[(a)]	Residential relocation[(a)]
Concurrent cyclone	-0.23	-0.08	0.97	0.41**	0.20	0.46	0.03	-0.11	7.11**	0.94
	[1.17]	[0.48]	[1.67]	[0.19]	[1.39]	[1.20]	[0.55]	[0.10]	[3.51]	[2.13]
Lagged cyclone	0.13	0.19	-0.50	0.30*	0.55	0.10	0.34	-0.08	-3.01***	0.73
	[0.88]	[0.42]	[1.18]	[0.18]	[1.15]	[1.11]	[0.69]	[0.13]	[1.03]	[2.61]
Observations	100,901	101,018	100,857	114,372	114,238	114,238	114,130	114,095	72,523	114,372
No of unique individuals	11,603	11,620	11,595	12,281	12,270	12,270	12,266	12,268	9,539	12,281
Overall R squared	0.23	0.71	0.23	0.80	0.46	0.73	0.15	0.65	0.21	0.29
Within R squared	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.04	0.00	0.01
Mean of dep. variable	6.63	70.09	13.36	1.26	54.50	47.61	1.62	1.86	2.05	21.79
Panel B:	Married[(a)]	Separated[(a)]	Fertility desires	Fertility intentions	Pregnancy[(a)]	Overall life satisfaction	Personal safety satisfaction	Health satisfaction	Residential insurance[(a)]	Health insurance[(a)]
Concurrent cyclone	-2.43*	1.25	-0.06	-0.00	-2.39*	-0.15***	-0.15**	-0.13**	5.29**	2.58*
	[1.39]	[0.85]	[0.15]	[0.14]	[1.37]	[0.05]	[0.06]	[0.06]	[2.69]	[1.38]
Lagged cyclone	-2.16*	2.00***	-0.01	0.14	1.52	-0.02	-0.15***	-0.01	1.93	3.37**
	[1.27]	[0.75]	[0.14]	[0.14]	[1.58]	[0.05]	[0.05]	[0.04]	[2.52]	[1.49]
Observations	114,372	114,372	97,496	97,192	100,945	114,335	114,292	114,322	77,259	67,694
No of unique individuals	12,281	12,281	11,529	11,511	11,602	12,277	12,276	12,276	10,024	9,190
Overall R squared	0.74	0.66	0.71	0.72	0.27	0.55	0.51	0.60	0.53	0.80
Within R squared	0.07	0.00	0.03	0.04	0.02	0.00	0.00	0.00	0.01	0.01
Mean of dep. variable	62.14	6.27	4.55	4.04	8.79	7.83	8.22	7.41	49.89	47.70

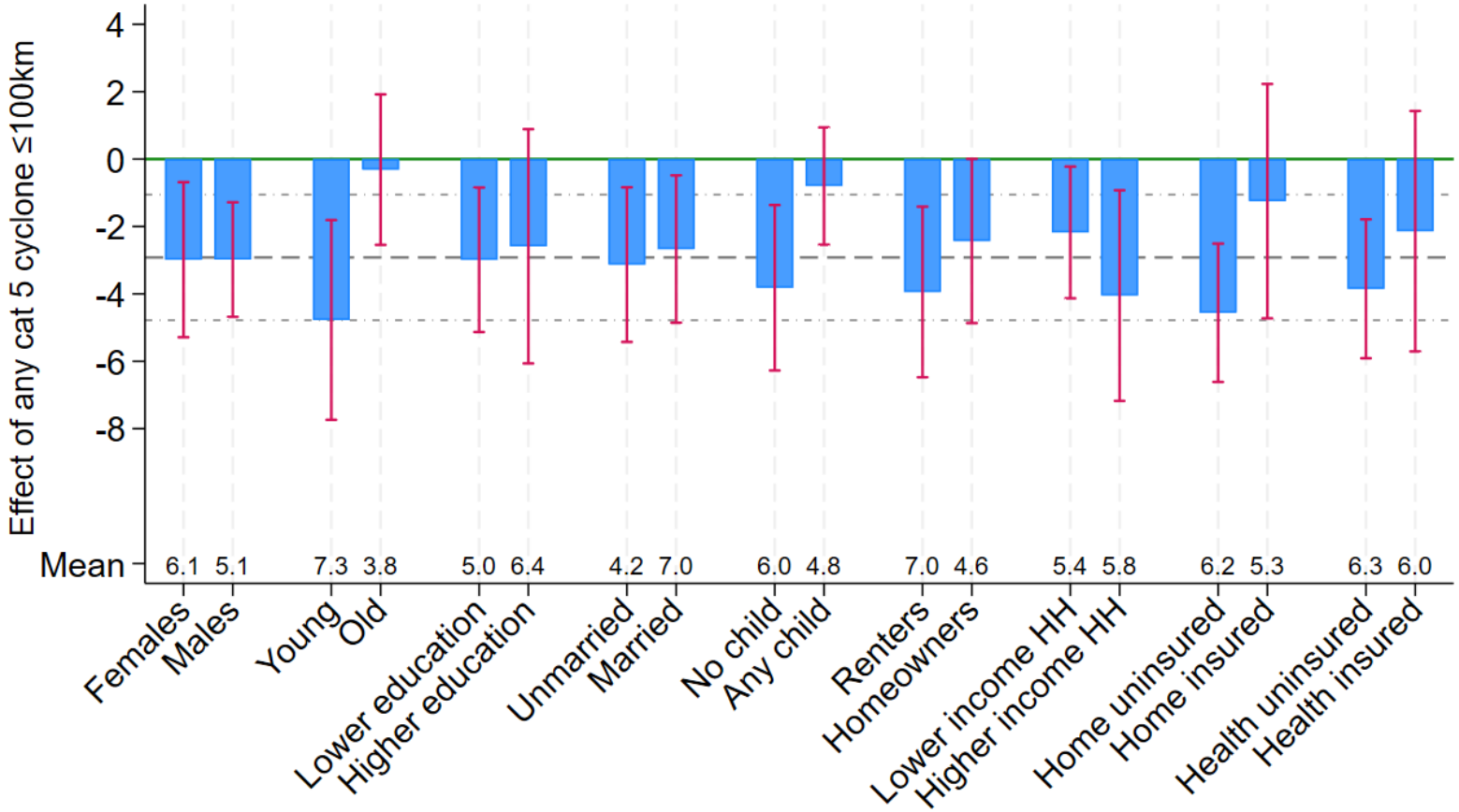
Notes: The results presented in each column and panel are based on a separate FE regression. Cyclone exposure measure: Concurrent and one-year lagged exposure to any category 5 cyclone within 100 km. Results (coefficient estimates, standard errors and sample means) for binary dependent variables, indicated by [(a)], are multiplied by 100 for aesthetic purposes. Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported 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: The blue line depicts the distribution of 1,000 regression estimates for the effect of randomly assigned exposure to a category 5 cyclone within 100 km of its eye, obtained from a modified version of Equation (1) in which postcode fixed effects are excluded. The vertical solid red line represents the coefficient estimate, while the long-dashed red lines indicate the 95% confidence intervals for exposure to a Category 5 cyclone within 100 km of its eye, obtained from the actual data using a similarly modified specification of Equation (1). The p-value is calculated as the probability that the estimate from the real data is smaller than or equal to the estimates from the randomized data. All estimates are multiplied by 100 for aesthetic purposes. We use the Stata command rndm, developed by Hsiang and Jina (2014), to implement the randomization procedure.

Figure 2: Heterogeneity in the cyclone impact on fertility - Separate regressions for each subgroup



Notes: The results (coefficient estimates, 95% confidence intervals, and sample means are multiplied by 100 for aesthetic purposes) for different sub-populations are obtained from a separate individual FE regression based on Equation (1). Dependent variable: Any newborn child. The estimated effect reflects the impact of current exposure to any category 5 cyclone within 100 km. 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. Detailed regression results are reported in Appendix Table A5.

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			Number of individuals affected
					Overall	Between	Within	
Age	The respondent's age at the survey time (years)	33.27	15.00	54.00	10.76	11.08	4.47	
Male	Dummy variable: = 1 if the individual is male, and zero otherwise	0.51	0.00	1.00	0.50	0.50	0.00	
NESB migrant	Dummy variable: = 1 if the individual was born overseas in a Non-English-Speaking Background (NESB) country, and zero otherwise	0.10	0.00	1.00	0.30	0.31	0.00	
ESB migrant	Dummy variable: = 1 if the individual was born overseas in an English-Speaking Background (ESB) country, and zero otherwise	0.08	0.00	1.00	0.27	0.28	0.00	
Year 12	Dummy: = 1 if the individual completes Year 12, and zero otherwise	0.19	0.00	1.00	0.39	0.34	0.21	
Vocational or Training qualification	Dummy: = 1 if the individual has a vocational or training qualification, and zero otherwise	0.35	0.00	1.00	0.48	0.44	0.19	
Bachelor or higher	Dummy: = 1 if the individual has a bachelor degree or higher, and zero otherwise	0.21	0.00	1.00	0.40	0.37	0.16	
Major city	Dummy variable: = 1 if the individual lives in a major city, and zero otherwise	0.62	0.00	1.00	0.49	0.46	0.20	
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	5.08	2.10	8.10	1.17	0.74	1.03	
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area	5.53	1.00	10.00	2.85	2.60	1.35	
Number of alive children	The difference between the number of children an individual has ever had and the number of children since died, both measured at the survey time	1.22	0.00	12.00	1.40	1.33	0.55	
Any newborn child	Dummy variable: = 1 if the individual has at least one child under the age of 1 at the time of the survey; 0 otherwise	0.06	0.00	1.00	0.23	0.10	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)	5.734	0.00	250.20	29.93	13.63	27.45	
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	0.012	0.00	1.00	0.11	0.05	0.10	1,571
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	0.005	0.00	1.00	0.07	0.03	0.07	665
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	0.06	0.03	0.06	551
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	0.014	0.00	1.00	0.12	0.04	0.11	1,892
Any category 5 cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any category 5 cyclone's eye last year, and zero otherwise	0.006	0.00	1.00	0.08	0.03	0.07	820

Notes: Sample of 133,384 year-observations from 14,274 unique persons.

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

Variable	Description	Mean	Standard deviations		
			Overall	Between	Within
Experience of serious personal illness	Dummy variable: = 1 if reporting "Serious personal injury or illness to self" to the question "Did any of these happen to you in the past 12 months?", and zero otherwise	0.07	0.25	0.16	0.22
General health	Short Form (SF)-36 summary score, a higher score indicating better health	70.32	19.61	16.96	11.14
Serious injury/illness to family member	Dummy variable: = 1 if reporting "Serious injury/illness to family member" to the question "Did any of these happen to you in the past 12 months?", and zero otherwise	0.14	0.34	0.21	0.30
Any deceased child	Dummy variable: = 1 if the individual has any deceased child at the time of the survey, and 0 otherwise	0.01	0.11	0.10	0.05
Equivalised household disposable income	Household disposable income from all sources, normalized by squared root of household size ($1,000, financial year, 2010 price)	53.80	43.89	31.22	33.41
Individual regular market income	Sum of financial year wages and salary, business income, investment income and regular private pension income ($1,000, financial year, 2010 price)	45.52	57.37	47.80	32.38
Individual non-wage irregular income	Sum of financial year inheritances, bequests, redundancy and severance payments, irregular transfers from non-resident parents, irregular payments from other non-household members, lump sum workers compensation and other irregular payments ($1,000, financial year, 2010 price)	1.55	23.09	10.91	21.44
Australian Government non-income support payments	Sum of 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 ($1,000, financial year, 2010 price)	1.77	3.87	2.87	2.44
Weather related home damage	Dummy variable: = 1 if reporting "A weather-related disaster (e.g. flood, bushfire, cyclone) damaged or destroyed your home" to the question "Did any of these happen to you in the past 12 months?", and zero otherwise.	0.02	0.14	0.08	0.13
Residential relocation	Dummy variable: = 1 if move address since last survey wave, and zero otherwise	0.23	0.42	0.25	0.37
Married	Dummy variable: = 1 if the individual is married or in de factor relationship at the survey time, and zero otherwise	0.61	0.49	0.44	0.28
Separated	Dummy variable: = 1 if the individual is separated/divorced/widowed at the survey time, and zero otherwise	0.06	0.24	0.20	0.15
Fertility desires	Response to the question "Would you like to have [a child of your own / more children] in the future?", a higher score indicating a greater likelihood	4.62	4.16	3.54	2.66

Variable	Description	Mean	Standard deviations		
			Overall	Between	Within
Fertility intentions	Response to the question "How likely are you to have [a child / more children] in the future?", a higher score indicating a greater probability	4.12	4.03	3.48	2.56
Pregnancy	Dummy variable: = 1 if reporting "Pregnancy / pregnancy of partner" to the question "Did any of these happen to you in the past 12 months?", and zero otherwise	0.09	0.28	0.16	0.25
Overall life satisfaction	Responses to the question “All things considered, how satisfied are you with your life?”, a higher score indicating greater life satisfaction	7.84	1.42	1.13	0.97
Personal safety satisfaction	Responses to the question the respondents about their satisfaction with how safe they feel, a higher score indicating greater satisfaction	8.22	1.59	1.21	1.15
Health satisfaction	Responses to the question the respondents about their satisfaction with their health, a higher score indicating greater satisfaction	7.46	1.84	1.50	1.21
Residential insurance	Dummy variable: = 1 if annual household expenditure on other insurance such as home, contents, motor vehicle ≥ $1,250, and zero otherwise	0.47	0.50	0.45	0.24
Private health insurance	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	0.49	0.50	0.38	0.36

Note: The sample size varies across variables, based on the sample used in the baseline regression.

Appendix Table A2: Remaining regression results on the determinants of fertility

Cyclone exposure measures:	Current	Current and one-year lagged	Current and two-year lagged	Current and one-year lead	Current category 5 cyclones
	(1)	(2)	(3)	(4)	(5)
Age 20-24 [(a)]	3.38***	3.39***	3.20***	3.65***	3.38***
	[0.34]	[0.36]	[0.36]	[0.38]	[0.34]
Age 25-29 [(a)]	7.25***	7.40***	7.37***	7.63***	7.25***
	[0.57]	[0.60]	[0.61]	[0.64]	[0.57]
Age 30-34 [(a)]	8.58***	8.74***	8.88***	9.05***	8.58***
	[0.83]	[0.89]	[0.91]	[0.90]	[0.83]
Age 35-39 [(a)]	3.72***	4.20***	4.30***	4.38***	3.72***
	[1.05]	[1.14]	[1.18]	[1.14]	[1.05]
Age 40-44 [(a)]	-1.04	-0.50	-0.43	-0.38	-1.04
	[1.22]	[1.33]	[1.37]	[1.34]	[1.22]
Age 45-49 [(a)]	-2.48*	-1.69	-1.27	-1.59	-2.48*
	[1.43]	[1.56]	[1.60]	[1.56]	[1.43]
Age 50-54 [(a)]	-3.18*	-2.10	-1.40	-2.12	-3.19*
	[1.65]	[1.80]	[1.85]	[1.81]	[1.65]
Year 12 [(b)]	-0.50*	-0.50*	-0.67*	-0.29	-0.50*
	[0.26]	[0.28]	[0.35]	[0.27]	[0.26]
Vocational or training qualification [(b)]	0.46	0.45	0.52	0.51	0.45
	[0.40]	[0.46]	[0.52]	[0.44]	[0.40]
Bachelor degree or higher [(b)]	0.72	0.94*	1.03*	0.91*	0.72
	[0.46]	[0.53]	[0.57]	[0.50]	[0.46]
Major city	2.10*	1.92*	1.64	2.48*	2.10*
	[1.10]	[1.12]	[1.16]	[1.27]	[1.10]
Local area unemployment rate	-0.07	-0.07	-0.15	-0.10	-0.06
	[0.14]	[0.15]	[0.17]	[0.15]	[0.14]
Local area SEIFA index	-0.22**	-0.20**	-0.18*	-0.22**	-0.22**
	[0.09]	[0.09]	[0.10]	[0.10]	[0.09]

Notes: The results (coefficient estimate and standard errors are multiplied by 100 for aesthetic purposes) presented in each column are based on a separate FE regression. Cyclone exposure measures are defined in the first row of this table, with their corresponding estimates reported in Table 2. Dependent variable: Any newborn child. Other explanatory variables include survey year dummies, month dummies, and postcode dummies. [(a)] and [(b)] indicates "Age 15-19" and "Under year 12 qualification" as the comparison group, respectively. Robust standard errors clustered at the postcode level are reported 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 cyclone 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)	-1.45*		2.00	14.21		
	[0.86]		[6.40]	[27.65]		
One-year lagged wind speed (km/h)	-0.38		4.47	21.47		
	[0.92]		[5.03]	[25.13]		
Logarithm of current wind speed		-1.66				
		[1.06]				
Logarithm of one-year lagged wind speed		-0.24				
		[1.11]				
Current wind speed squared			-0.01	-0.10		
			[0.02]	[0.19]		
Lagged wind speed squared			-0.02	-0.14		
			[0.02]	[0.18]		
Current wind speed cubed				0.00		
				[0.00]		
Lagged wind speed cubed				0.00		
				[0.00]		
Current any cyclone exposure					-0.77	
					[0.55]	
Lagged any cyclone exposure					0.43	
					[0.58]	
Current wind speed ≥ 50 and < 100 km						0.33
						[1.04]
Current wind speed ≥ 100 and < 150 km						-1.04
						[1.23]
Current wind speed ≥ 150 and < 200 km						-0.72
						[0.86]
Current wind speed ≥ 200 km						-3.42***
						[1.18]
Lagged wind speed ≥ 50 and < 100 km						0.73
						[1.02]
Lagged wind speed ≥ 100 and < 150 km						0.91
						[1.14]
Lagged wind speed ≥ 150 and < 200 km						0.35
						[0.93]
Lagged wind speed ≥ 200 km						-0.26
						[1.24]
Observations	114,372	114,372	114,372	114,372	114,372	114,372
Number of unique individuals	12,281	12,281	12,281	12,281	12,281	12,281
Overall R squared	0.17	0.17	0.17	0.17	0.17	0.17
Within R squared	0.01	0.01	0.01	0.01	0.01	0.01

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: 114,372 observations (12,281 unique persons). Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode 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 are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A4: Determinants of attrition

Dependent variable:	Attrition due to any reason
	(1)
Current category 1	-1.06
	[0.80]
Current category 2	0.16
	[1.49]
Current category 3	-0.84
	[1.17]
Current category 4	0.39
	[0.68]
Current category 5	-1.28
	[0.91]
One-year lagged category 1	-0.68
	[0.81]
One-year lagged category 2	-0.44
	[1.15]
One-year lagged category 3	2.80*
	[1.46]
One-year lagged category 4	-0.09
	[0.70]
One-year lagged category 5	0.13
	[1.09]
Age 20-24 [(a)]	2.45***
	[0.45]
Age 25-29 [(a)]	1.76***
	[0.65]
Age 30-34 [(a)]	0.75
	[0.77]
Age 35-39 [(a)]	0.16
	[0.96]
Age 40-44 [(a)]	-0.55
	[1.16]
Age 45-49 [(a)]	-1.39
	[1.36]
Age 50-54 [(a)]	-1.49
	[1.59]
Year 12 [(b)]	3.71***
	[0.46]
Vocational or training qualification [(b)]	2.55***
	[0.54]
Bachelor degree or higher [(b)]	2.81***
	[0.63]
Observations	111,330
Number of unique individuals	13,964
Mean of dependent variable (%)	6.79
R squared	0.04
P value (Wald test)	0.42

Notes: Results are from an individual FE regression similar to Equation (1). Results (coefficient estimates, standard errors and sample mean) are multiplied by 100 for aesthetic purposes. [(a)] and [(b)] indicates "Age 15-19" and "Under year 12 qualification" 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, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A5: Heterogeneity in the impact of exposure to any category 5 cyclone on fertility - Separate regressions for each subgroup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Separate regression by:	Gender		Age		Education		Marital status		Family size	
	Female	Male	Young	Old	Lower	Higher	Unmarried	Married	No child	Any child
Any category 5 cyclone within 100 km	-2.99**	-2.98***	-4.77***	-0.31	-2.99***	-2.59	-3.13***	-2.67**	-3.82***	-0.80
	[1.17]	[0.87]	[1.51]	[1.14]	[1.09]	[1.77]	[1.17]	[1.11]	[1.25]	[0.89]
Observations	64,987	68,312	67,776	64,827	78,421	54,912	66,179	67,137	86,575	46,755
No of unique individuals	6,983	7,287	9,322	7,788	8,332	5,941	6,916	7,354	9,047	5,225
Overall R squared	0.17	0.17	0.22	0.21	0.17	0.18	0.15	0.19	0.16	0.25
Within R squared	0.02	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.02
Mean of dep. variable	6.09	5.13	7.25	3.81	5.05	6.39	4.19	6.98	6.02	4.81
Proportion affected (%)	0.61	0.61	0.67	0.56	0.65	0.56	0.61	0.62	0.64	0.56
Panel B: Separate regression by:	Home ownership		Household income		Residential insurance		Health insurance			
	Renter	Owner	Poorer	Richer	Uninsured	Insured	Uninsured	Insured		
Any category 5 cyclone within 100 km	-3.94***	-2.43*	-2.18**	-4.05**	-4.56***	-1.25	-3.85***	-2.14		
	[1.29]	[1.24]	[1.00]	[1.59]	[1.05]	[1.77]	[1.05]	[1.82]		
Observations	55,174	78,130	80,694	52,634	69,352	52,421	60,133	51,626		
No of unique individuals	6,145	8,119	8,249	6,021	6,468	4,667	5,590	4,466		
Overall R squared	0.18	0.17	0.18	0.18	0.17	0.17	0.17	0.16		
Within R squared	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02		
Mean of dep. variable	6.95	4.65	5.44	5.84	6.19	5.30	6.30	6.04		
Proportion affected (%)	0.78	0.50	0.66	0.55	0.70	0.56	0.75	0.61		

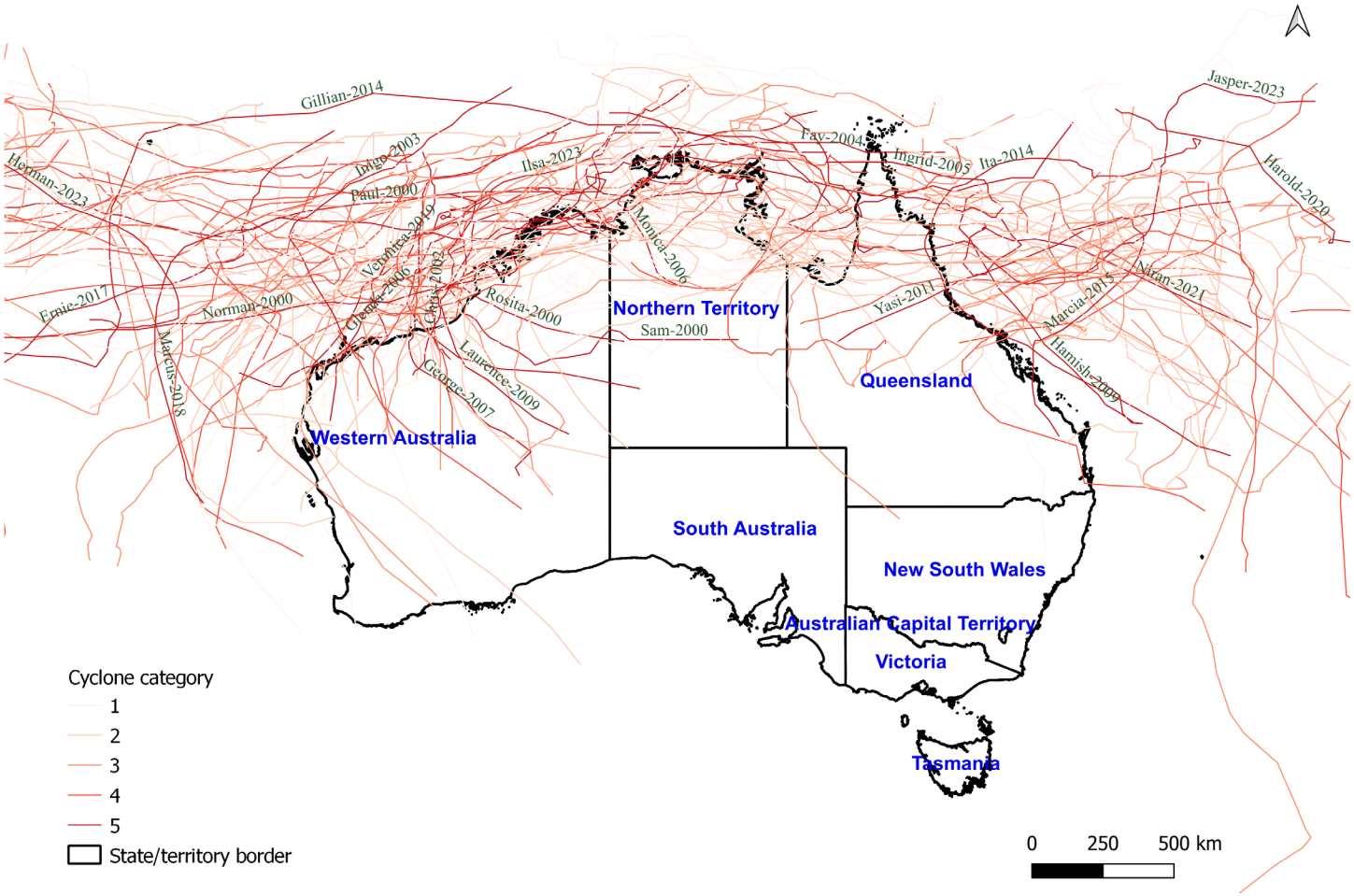
Notes: The results (coefficient estimate, standard errors, and sample means are multiplied by 100 for aesthetic purposes) in each column and panel are derived from separate individual FE regressions based on Equation (1). The estimated effect reflects the impact of current exposure to any category 5 cyclone within 100 km. "Proportion affected" represents the share of individuals in the sample who experienced a category 5 cyclone within 100 km during the 12 months preceding the survey. Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A6: Dynamics of cyclone impacts on fertility by subgroup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Separate regression by:	Gender		Age		Education		Marital status		Family size	
	Female	Male	Young	Old	Lower	Higher	Unmarried	Married	No child	Any child
Current category 5	-3.17**	-2.53**	-5.22***	0.02	-3.86***	-1.21	-3.63***	-1.79	-3.83***	-1.33
	[1.40]	[1.12]	[1.82]	[1.32]	[1.28]	[2.18]	[1.36]	[1.40]	[1.48]	[0.99]
One-year lagged category 5	-0.71	-0.77	-0.83	-0.21	-1.59	0.98	-0.84	-0.33	-1.32	0.44
	[1.56]	[1.37]	[2.16]	[1.41]	[1.31]	[2.08]	[1.45]	[1.82]	[1.75]	[1.59]
Two-year lagged category 5	1.15	0.96	1.76	0.46	1.72	0.19	1.74	0.45	1.10	0.50
	[1.92]	[1.82]	[2.48]	[2.00]	[1.93]	[2.86]	[1.95]	[2.30]	[2.31]	[2.12]
Observations	48,492	50,795	45,728	53,004	57,914	41,397	48,989	50,319	64,756	34,546
No of unique individuals	5,294	5,526	6,559	6,475	6,294	4,524	5,233	5,587	6,865	3,951
Overall R squared	0.18	0.18	0.22	0.22	0.18	0.19	0.16	0.21	0.17	0.21
Within R squared	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01
Mean of dep. variable	6.30	5.25	8.02	3.75	5.32	6.37	5.02	6.48	7.07	3.31
Proportion affected (%)	0.68	0.66	0.73	0.62	0.71	0.62	0.66	0.68	0.68	0.65
Panel B: Separate regression by:	Home ownership		Household income		Residential insurance		Health insurance			
	Renter	Owner	Poorer	Richer	Uninsured	Insured	Uninsured	Insured		
Current category 5	-4.88***	-1.45	-2.34*	-4.19**	-4.82***	0.14	-3.73***	-2.15		
	[1.47]	[1.49]	[1.24]	[1.96]	[1.20]	[2.09]	[1.24]	[2.24]		
One-year lagged category 5	-3.10*	1.24	-1.11	0.09	-1.08	1.21	-1.32	0.11		
	[1.78]	[1.46]	[1.55]	[2.17]	[1.43]	[2.16]	[1.60]	[2.02]		
Two-year lagged category 5	-0.89	2.60	1.59	0.14	0.84	2.31	2.32	-0.69		
	[2.02]	[2.66]	[1.59]	[3.14]	[2.31]	[2.70]	[2.11]	[2.56]		
Observations	40,778	58,519	60,767	38,540	53,728	41,444	46,458	41,215		
No of unique individuals	4,546	6,273	6,377	4,441	5,522	4,135	4,625	3,891		
Overall R squared	0.19	0.18	0.18	0.19	0.18	0.18	0.18	0.18		
Within R squared	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.02		
Mean of dep. variable	7.01	4.89	5.32	6.45	6.23	5.46	6.24	6.26		
Proportion affected (%)	0.85	0.55	0.73	0.57	0.74	0.59	0.79	0.64		

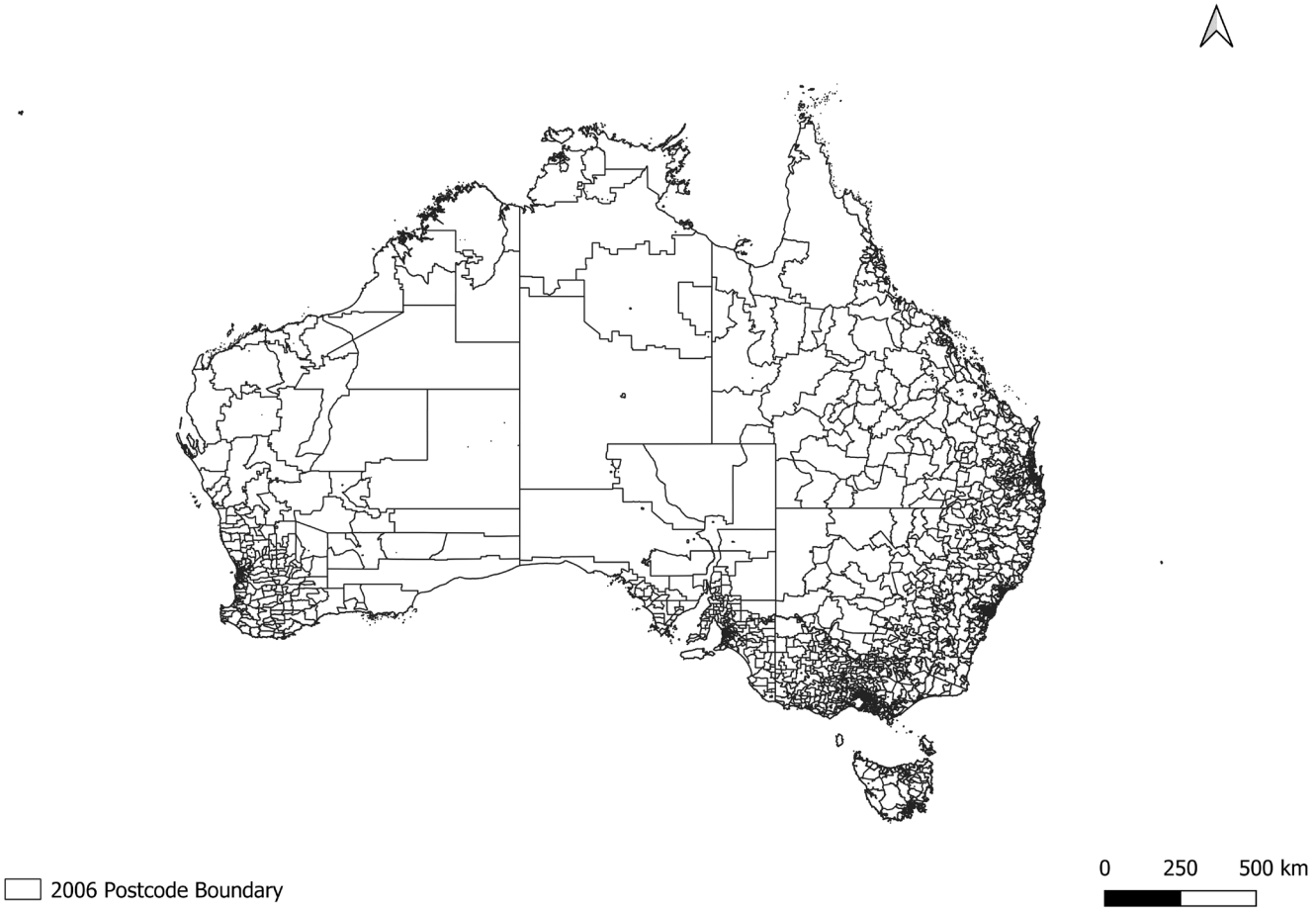
Notes: The results (coefficient estimate, standard errors, and sample means are multiplied by 100 for aesthetic purposes) in each column and panel are derived from separate individual FE regressions based on Equation (1). The estimated effect reflects the impact of exposure to any category 5 cyclone within 100 km. "Proportion affected" represents the share of individuals in the sample who experienced a category 5 cyclone within 100 km during the 12 months preceding the survey. Other explanatory variables include age groups, education, major city residency, local area socio-economic variables, survey year dummies, month dummies, and postcode dummies. Robust standard errors clustered at the postcode level are reported in squared brackets. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Figure A1: Tropical cyclone hit map between 2000 and 2024



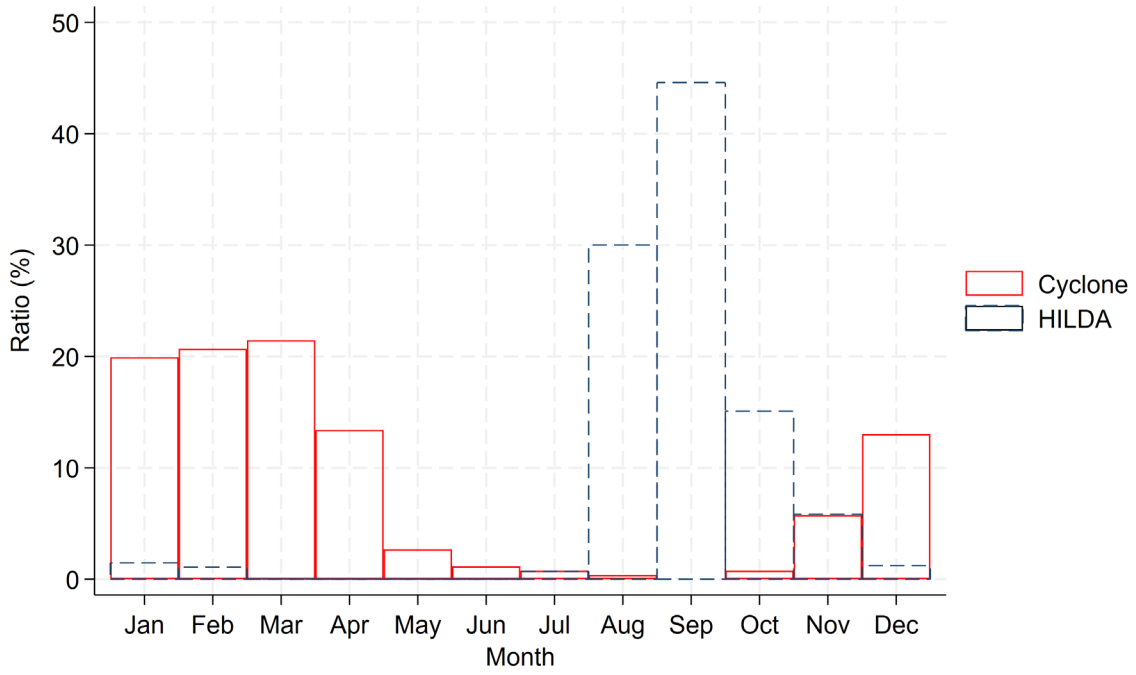
Notes: Cyclone category is classified using the maximum mean wind speed cut-offs from BOM. Cyclones are available up to December 2024. Only the names and years of category 5 cyclones are shown.

Appendix Figure A2: 2006 postal code boundaries in Australia



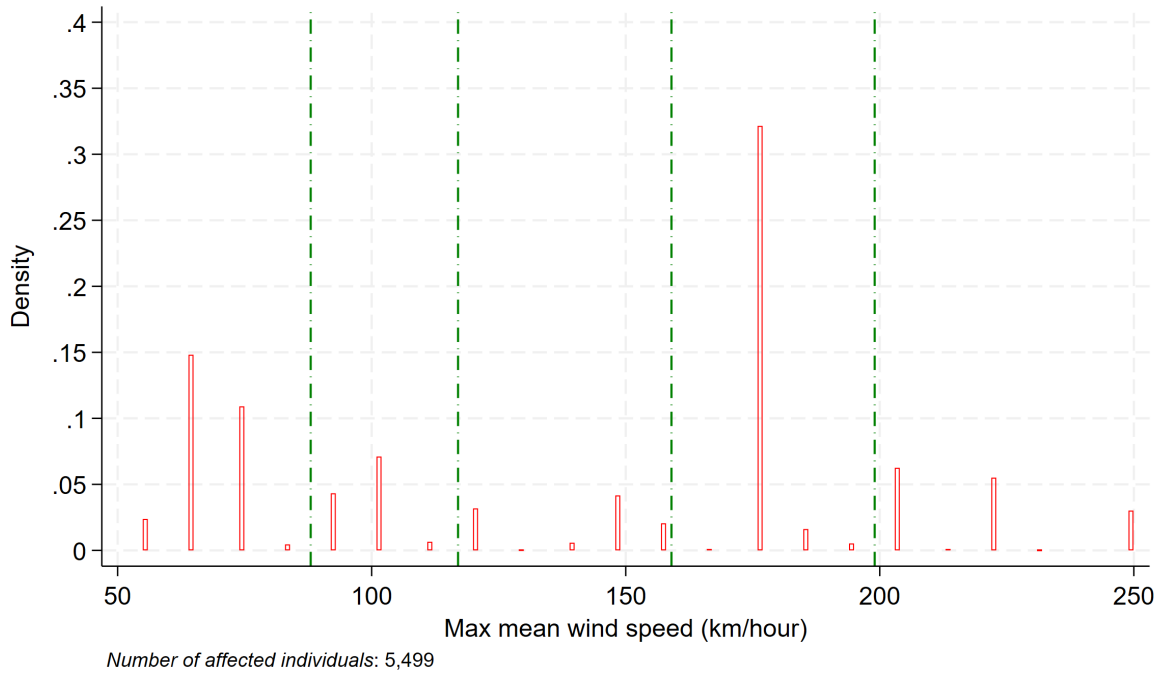
Notes: Postal Areas 2006 shapefile is obtained from the Australian Bureau of Statistics.

Appendix Figure A3: Distribution of cyclone occurrence and HILDA interview dates



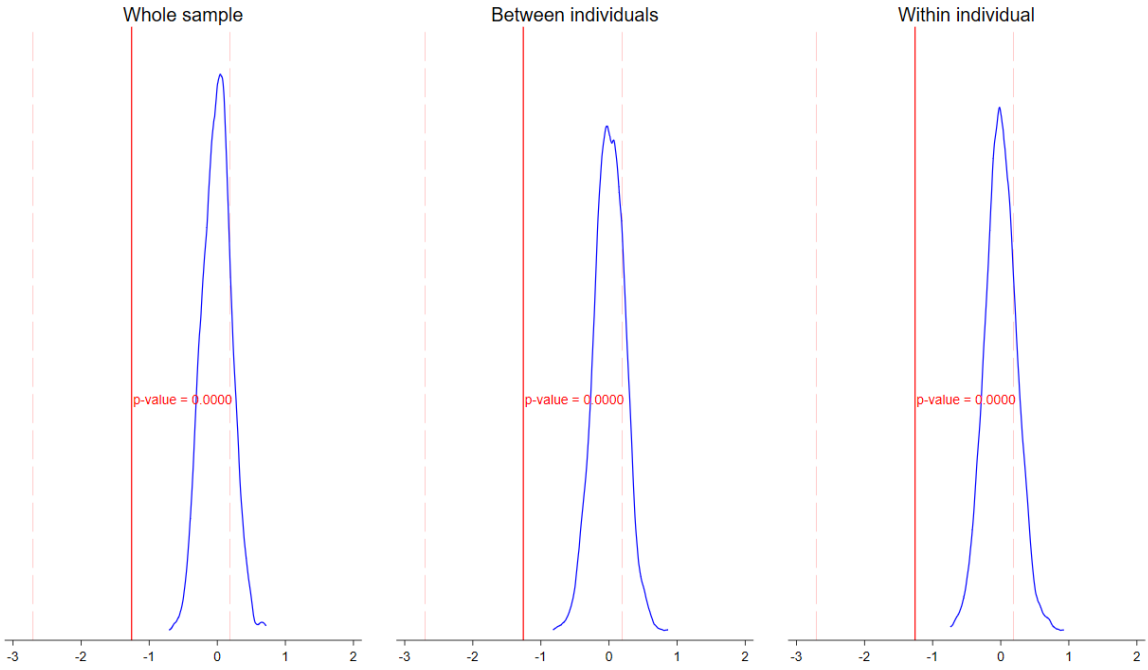
Notes: Data from historical tropical cyclone observed from 2000 to December 2024 and HILDA Release 23.

Appendix Figure A4: Distribution of maximum wind speed of cyclones



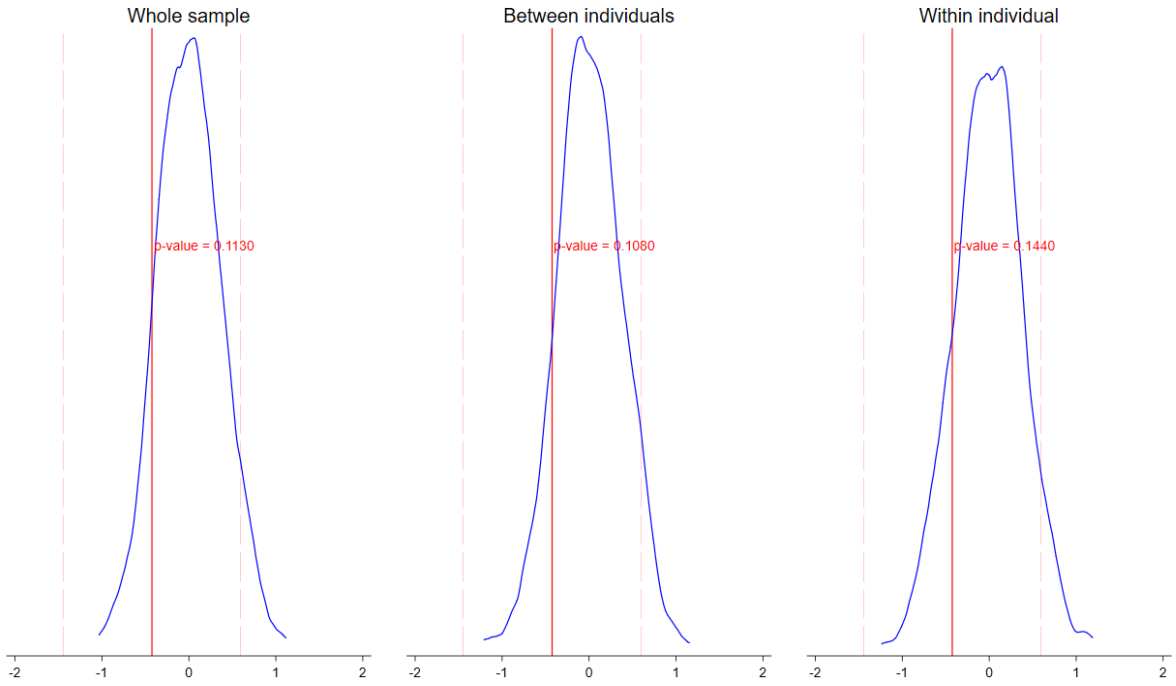
Notes: This figure illustrates the distribution of wind speed across all years for individuals in our final sample who have ever been exposed to a cyclone within 100 km of their residential postcode centroid. The vertical dashed-dotted green lines represent the maximum mean wind speed thresholds prescribed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

Appendix Figure A5: Randomization tests for continuous maximum wind speed of cyclones



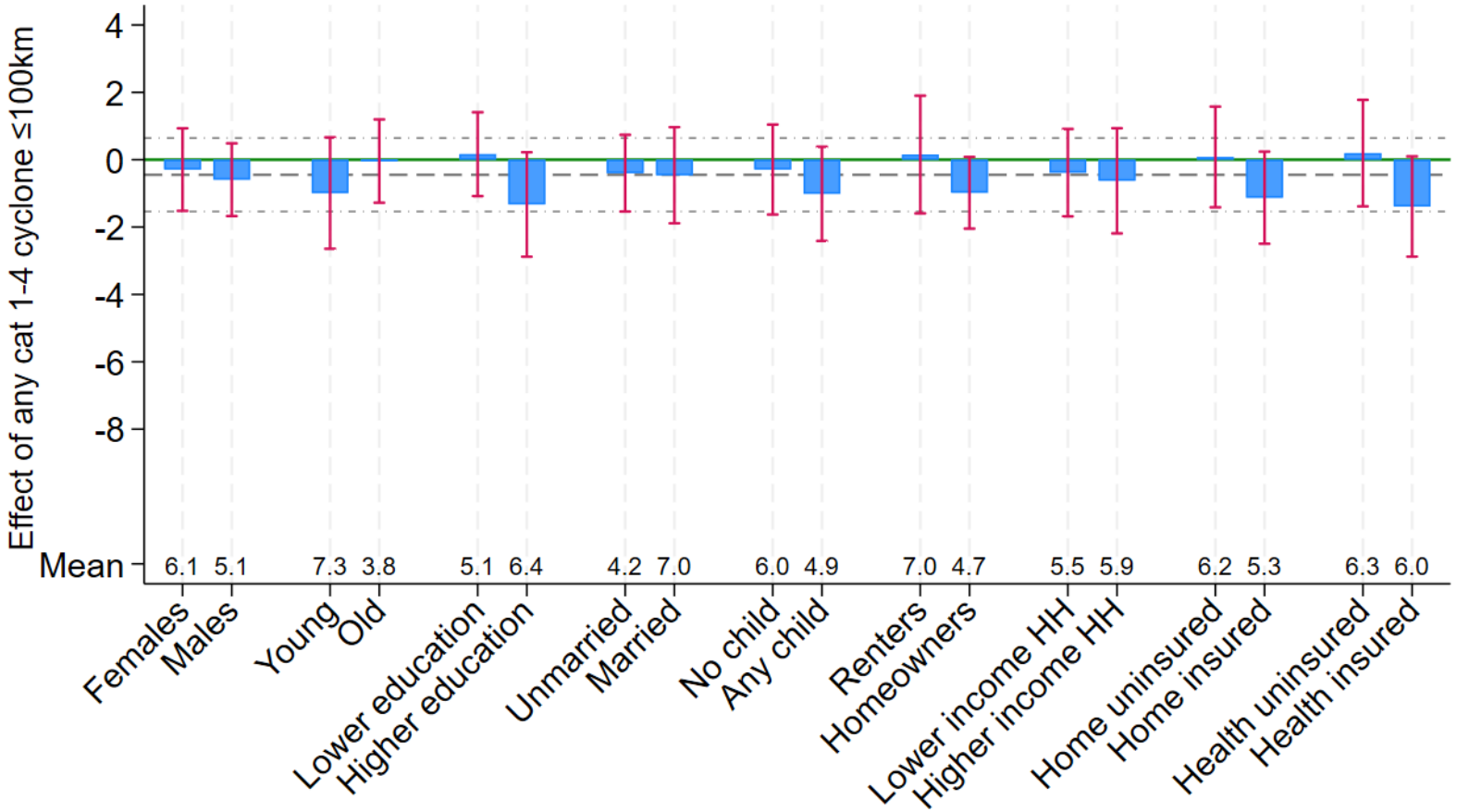
Notes: The blue line depicts the distribution of 1,000 regression estimates of continuous maximum wind speed (in km/h) for cyclones within 100 km of their eye. The estimates are obtained from a modified specification of Equation (1), in which postcode fixed effects are excluded and an additional dummy variable indicating areas unaffected by any cyclone is included. The vertical solid red line represents the observed effect, while the long-dashed red lines denote the 95% confidence intervals of continuous maximum wind speed for cyclones within 100 km of their eye. These estimates are obtained from the actual data using a similarly modified specification of Equation (1). The p-value is calculated as the probability that the estimate from the real data is smaller than or equal to the estimates from the randomized data. All estimates are multiplied by 10,000 for aesthetic purposes. We use the Stata command rndm, developed by Hsiang and Jina (2014), to implement the randomization procedure.

Appendix Figure A6: Randomization tests for exposure to Category 1–4 cyclones



Notes: The blue line depicts the distribution of 1,000 regression estimates for the effect of randomly assigned exposure to a Category 1–4 cyclone within 100 km of its eye, obtained from a modified version of Equation (1) in which postcode fixed effects are excluded. Individuals exposed to any Category 5 cyclones are excluded from these randomizations. The vertical solid red line represents the coefficient estimate, while the long-dashed red lines indicate the 95% confidence intervals for exposure to a Category 1–4 cyclone within 100 km of its eye, obtained from the actual data using a similarly modified specification of Equation (1). The p-value is calculated as the probability that the estimate from the real data is smaller than or equal to the estimates from the randomized data. All estimates are multiplied by 100 for aesthetic purposes. We use the Stata command rndm, developed by Hsiang and Jina (2014), to implement the randomization procedure.

Appendix Figure A7: Heterogeneity in the impact of exposure to Category 1–4 cyclones on fertility - Separate regressions for each subgroup



Notes: The results (coefficient estimates, 95% confidence intervals, and sample means are multiplied by 100 for aesthetic purposes) for different sub-populations are obtained from a separate individual FE regression based on Equation (1). Dependent variable: Any newborn child. The estimated effect reflects the impact of current exposure to any category 1 to 4 cyclone within 100 km. Individuals exposed to any Category 5 cyclones are excluded from these analyses. 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.