Extreme weather events, home damage, and the eroding locus of control

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The catastrophic consequences of natural disasters on social and economic systems are extensively documented, yet their influence on individuals' sense of control over their life outcomes remains unexplored. This study pioneers an investigation into the causal effects of natural disaster-related home damage on the locus of control. Utilizing Australian longitudinal data, we implement an individual fixed effects instrumental variables approach leveraging time-varying, exogenous exposure to local cyclones to address confounding factors. Our findings provide robust evidence that natural disaster-induced home damage statistically significantly and substantially diminishes individuals' perception of control, particularly for those at the lower end of the locus of control distribution. This effect is disproportionately pronounced among older individuals, renters, and those from lower-income households. This newfound understanding offers opportunities for developing targeted interventions and support mechanisms to enhance resilience and assist these vulnerable populations following natural disasters.

Keywords: Natural Disasters; Locus of Control; Housing; Australia

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1. Introduction

Natural disasters have demonstrably profound social and economic consequences on a global scale (Dell *et al.* 2014; Carleton & Hsiang 2016). As concerns over the increasing frequency and intensity of natural disasters escalate, research examining their psychological impacts has gained significant momentum (Currie & Rossin-Slater 2013; Nguyen & Mitrou 2024a). However, a critical gap exists in our understanding of how natural disasters influence individuals' Locus of Control (LoC). Locus of control, defined as the belief in one's ability to influence life outcomes (Rotter 1966), has been shown to be associated with various socio-economic outcomes (Almlund *et al.* 2011; Heckman & Kautz 2012) and may play a crucial role in shaping coping mechanisms and resilience. Investigating how natural disasters impact individuals' perception of control over their lives is vital for developing effective disaster preparedness and recovery strategies, especially as we enter an era of climatic uncertainty with forecasts of increased climate-induced extreme weather events.

This study aims to address this gap by being the first to investigate the causal effects of natural disaster-induced home damage on locus of control. In doing so, it intersects with two main lines of research. The first, and highly established, line focuses on the social and economic impacts of natural disasters (Dell *et al.* 2014; Carleton & Hsiang 2016; Botzen *et al.* 2019). Within this research area, our study closely aligns with the growing body of work evaluating the effects of natural disasters on various psychological aspects, including risk preferences (Cameron & Shah 2015; Hanaoka *et al.* 2018; Bourdeau-Brien & Kryzanowski 2020), religious beliefs (Belloc *et al.* 2016; Bentzen 2019), mental health (Currie & Rossin-Slater 2013; Baryshnikova & Pham 2019), and life satisfaction (Gunby & Coupé 2023; Nguyen & Mitrou

2024a).[1] However, no study has yet explored the impacts of natural disasters on LoC, which constitutes the specific focus of this research.

This study also aligns with a burgeoning body of literature investigating the relationship between LoC and various life outcomes. Prior empirical research demonstrates that individuals with an internal LoC, who believe their outcomes are contingent on their own actions, exhibit superior results in areas such as labour market success, finances, health, and education. For instance, individuals with an internal LoC tend to have higher wages (Cobb-Clark 2015), engage in more intensive job searches when unemployed (Caliendo *et al.* 2015), adopt healthier behaviours (Cobb-Clark *et al.* 2014; Kesavayuth *et al.* 2020), save more money (Cobb-Clark *et al.* 2016), purchase greater insurance coverage (Antwi-Boasiako 2017; Bonsang & Costa-Font 2022), hold more risky assets (Salamanca *et al.* 2020), and invest more in education (Coleman & DeLeire 2003; Caliendo *et al.* 2022) compared to those with an external LoC. Additionally, research suggests that individuals with a stronger internal LoC exhibit greater coping abilities in the face of negative events, such as job losses, health shocks, local crimes or natural disasters (Buddelmeyer & Powdthavee 2016; Schurer 2017; Etilé *et al.* 2021; Churchill & Smyth 2022; Güzel *et al.* 2024).

It is important to note that, consistent with established theoretical models and earlier empirical evidence (Rotter 1966; Borghans *et al.* 2008; Heckman & Kautz 2012; Cobb-Clark & Schurer 2013), these prior studies largely treat LoC as a fixed and exogenous variable within the analysed timeframe (see Nguyen *et al.* (2024b) for a recent review). However, recent studies utilizing panel data have shown that LoC can be influenced by certain life events, including changes in employment status or health (Elkins *et al.* 2017; Preuss & Hennecke 2018;

[1] This study extends the body of research utilizing the same dataset as three prior studies, which investigate the effects of cyclones on residential responses (Nguyen & Mitrou 2024b), life satisfaction (Nguyen & Mitrou 2024a), and the demand for health insurance (Nguyen & Mitrou 2025). However, none of these studies have examined the impact of weather-related home damage on LoC, a focus uniquely addressed in the present paper.

Marsaudon 2022; Clark & Zhu 2024; Nguyen *et al.* 2024b). This present study uniquely contributes to this field by investigating whether exposure to natural disasters causally influences individuals' LoC.

To quantify the causal effects of natural disaster-induced home damage on individuals' LoC, this study leverages longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, which contains a self-reported measure of natural disaster-related home damage and person-level LoC. We address the potential endogeneity of self-reported natural disaster-related home damage by employing an individual fixed effects instrumental variables (FE-IV) approach. This approach exploits within-individual time variation in exogenous exposure to local cyclones as an instrument for natural disaster-related home damage. We apply this FE-IV model to explore the heterogeneous effects of home damage across the distribution of LoC, in addition to the average effect.

The study yields three main sets of findings. First, we observe a statistically significant negative impact of weather-related home damage on internal LoC, meaning natural disaster-induced home damage significantly diminishes individuals' sense of control over their life outcomes. This effect is only evident in the quantile FE-IV regressions, where individuals near or below the median of the LoC distribution experience the most pronounced decline following natural disaster-related home damage. Moreover, the negative impact is strongest for those at the lowest end of the LoC distribution, where weather-related home damage reduces their LoC by 0.28 standard deviations.

Second, our analysis reveals significant heterogeneity in the impact of weather-related home damage on LoC across selected sociodemographic groups. This heterogeneity varies along the LoC distribution, with a general trend indicating a more pronounced negative effect for older individuals, renters, and those residing in poorer households.

Third, our findings demonstrate robustness to a battery of sampling and specification tests. Furthermore, the study underscores the importance of addressing the endogeneity of self-reported natural disaster-related home damage when estimating its impact on LoC. Additionally, and importantly, our results highlight the value of examining the effects of natural disaster exposure beyond the mean of the LoC distribution. Focusing solely on the average impact would risk overlooking the severe consequences of natural disasters on individuals' LoC, particularly for those at the lower end of the LoC distribution.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the primary data source used in the analysis. Section 3 details the econometric models employed to quantify the causal impact of weather-related home damage on individuals' LoC. Section 4 presents the key empirical results of the study. Section 5 documents the findings from various sensitivity tests conducted to assess the robustness of the results. Section 6 explores the potential heterogeneity in the impacts of weather-related home damage on LoC across different subgroups. Finally, Section 7 concludes the paper by summarizing the main findings and discussing their implications.

2. Data and sample

2.1. Data

Our primary data source is the Household, Income and Labour Dynamics in Australia (HILDA) survey. This nationally representative survey tracks individuals from private households over time, offering comprehensive individual and household-level data, including residential information, health outcomes, and labour market experiences (Summerfield *et al.* 2024). A key advantage of HILDA is its ability to follow individuals who relocate, thus preserving the sample's representativeness. This feature allows us to employ an individual fixed effects model to robustly examine the impact of natural disaster exposure on locus of control. We use the most recent release 23 of HILDA survey, covering the period from 2001 to 2023.

2.2. Natural disaster exposure measure

Individuals are classified as directly impacted by a natural disaster if they report that their residence sustained damage or destruction due to a weather-related disaster, such as a flood, bushfire, or cyclone, within the preceding 12 months. This categorization is based on responses to a survey question asking, "Did any of these events occur to you in the past 12 months?" specifically prompting, "A weather-related disaster (e.g., flood, bushfire, cyclone) damaged or destroyed your home".

Australian research has frequently used this variable as a proxy for direct exposure to natural disasters, examining its effects on mental health (Baryshnikova & Pham 2019), economic outcomes (Johar *et al.* 2022), life satisfaction (Gunby & Coupé 2023; Nguyen & Mitrou 2024a), and residential responses (Nguyen & Mitrou 2024b). This measure is available only from Wave 9 onwards (Summerfield *et al.* 2024). Consistent with previous Australian studies, this study employs the self-reported home damage indicator in the main analysis to capture the effects of direct exposure to natural disasters. This measure is distinct from an *indirect* exposure indicator, which classifies individuals as affected based on their residence in a disaster-impacted area, recognizing that not all residents in such areas are *directly* affected by the disaster (Johar *et al.* 2022). In subsequent sections, we further examine the effects of indirect exposure to a prevalent type of natural disaster—cyclones—which are also referenced in the survey prompt as a climatic factor associated with home damage and serve as our instrumental variable.

2.3. Locus of control measure

The locus of control measure in the HILDA survey is constructed from respondents' responses to seven statements. These statements are: (1) "I have little control over the things that happen to me", (2) "There is really no way I can solve some of the problems I have", (3) "There is little I can do to change many of the important things in my life", (4) "I often feel helpless in dealing with the problems of life", (5) "Sometimes I feel that I'm being pushed around in life", (6) "What happens to me in the future mostly depends on me", and (7) "I can do just about anything I really set my mind to do".

The first five statements (1-5) measure external control, while the last two (6-7) refer to internal control. For each statement, respondents indicate their level of agreement or disagreement on a scale from 1 ("Strongly disagree") to 7 ("Strongly agree"). Appendix Figure A1 illustrates the distribution of responses for each statement, revealing a strong left skew for the five statements measuring external control and a right skew for the two statements assessing internal control. To ensure consistency of responses across all seven statements, the responses to the first five statements are reverse-coded so that a higher score indicates a greater sense of control. Following prior Australian research using the same HILDA data (Cobb-Clark & Schurer 2013; Buddelmeyer & Powdthavee 2016; Elkins *et al.* 2017; Nguyen *et al.* 2024b), a summary score is constructed by aggregating the reverse-coded scores from the first five statements with the scores from the last two statements. Thus, the summary score of LoC ranges from 7 to 49, with a higher score indicating a greater sense of personal control over life outcomes, and vice-versa. Furthermore, to facilitate interpretation of the results, this LoC summary score is standardized to have a mean of zero and a standard deviation of one (Nguyen *et al.* 2024b).[2] A higher score on this standardized LoC measure still indicates a greater sense of control over life. In the current release 23 of HILDA, the LoC measure is only available in Waves 3, 4, 7, 11, 15, 19 and 23.

2.4. Sample

[2] Because we will use different samples throughout this paper, for comparability purposes, the summary score of LoC is standardized using all valid LoC summary scores of all individuals observed in Release 23 of HILDA. The unstandardized sample mean is 37.82, with a raw standard deviation of 8.05. This approach may result in means or standard deviations of the standardized scores that are not exactly zero or one, respectively, for certain samples, including the main sample.

The unit of analysis in this paper is the individual, as both the LoC and natural disaster exposure measures are recorded at the individual level. We restrict the sample to survey waves that include both LoC and natural disaster exposure measures. Consequently, our sample encompasses four HILDA waves: 11, 15, 19 and 23. Additionally, we require individuals to be observed at least twice within the study period, as our primary empirical model relies on individual fixed effects. By combining these restrictions, the final sample size consists of 53,778 individual-year observations from 16,687 unique individuals,[3] each observed for up to nine years. During this period, LoC data were collected in 2011, 2015, 2019, and 2023, allowing for an examination of the impact of weather-related home damage on LoC.

3. Empirical model

We employ the following econometric model to investigate the effects of weather-related home damage on locus of control Y of individual i at time t:

$$Y_{it} = \alpha_1 + \beta_1 D_{it} + X_{it}\gamma_1 + \delta_i + \varepsilon_{1it} \quad (1)$$

where D_{it} is a binary variable capturing whether the individual's home was damaged or destroyed by a weather-related event. X_{it} is a set of time-variant explanatory variables. δ_i captures individual time-invariant unobservable factors and ε_{1it} denotes the usual idiosyncratic term. α_1, β_1 and γ_1 are parameters to be estimated.

In equation (1), β_1 is the parameter of interest, which captures the effect of home damage on the individual's locus of control. While the above individual fixed effects (FE) regression model (1) controls for individual time-invariant unobserved characteristics, such as genetic

[3] These individuals come from 15,478 unique households, with an average of approximately 1.7 members per household included in the same survey wave during the study period. The small household size, along with the fact that HILDA does not identify the household head—who is typically considered the principal income earner in household surveys (Summerfield *et al.* 2024)—precludes a rigorous analysis of potential differential impacts based on individuals' roles within their households. Similarly, we do not explore potential inter-correlation in LoC among household members due to the absence of a suitable identification strategy to address the endogeneity of each household member's LoC.

factors or residential preferences, it cannot deal with issues associated with reverse causality, unobservable time-variant factors correlating with both LoC and home damage, and measurement errors (Wooldridge 2010). Specifically, it is unclear whether self-reported home damage changes the individual's LoC or individuals with a different sense of control have differential tendency to report weather-related home damage. There is also a concern that there are some individual unobservable time-variant factors, such as health shocks, correlate with both LoC and home damage at the same time. Moreover, while the respondent was asked to report any home damage, the magnitude of such a damage, if any, is not reported. These factors, in isolation or combination, can lead to bias in the FE estimates (Wooldridge 2010; Nguyen *et al.* 2024a).

As such, the estimate of β from equation (1) may not capture the true causal impact of home damage on one's locus of control. We employ the following auxiliary equation in an instrumental variables (IV) approach to investigate whether the individual i reports any weather-related home damage:

$$D_{it} = \alpha_2 + \sigma Z_{it} + X_{it}\gamma_2 + \delta_i + \varepsilon_{2it} \qquad (2)$$

where Z_{it} is an instrumental variable, ε_{2it} is an error term, and α_2, σ and γ_2 are vectors of parameters to be estimated. X_{it} and δ_i are defined as in Equation (1).

Motivated by prior studies that have successfully used climatic events as instruments for potentially endogenous treatment variables in various contexts (Belasen & Polachek 2008; Imberman *et al.* 2012; Baker & Bloom 2013; Barrot & Sauvagnat 2016; Dessaint & Matray 2017; Bernile *et al.* 2023),[4] we employ a weather-related variable as an instrument for the weather-related home damage variable. Specifically, we utilize a time-varying variable

[4] For instance, natural disasters have been used in previous research to instrument for temporary shocks to local labour markets (Belasen & Polachek 2008), school displacement (Imberman *et al.* 2012), uncertainty (Baker & Bloom 2013), suppliers' output (Barrot & Sauvagnat 2016), risk perception (Dessaint & Matray 2017), and local demand shocks (Bernile *et al.* 2023).

indicating whether an individual was affected by a cyclone in the preceding year as an instrument to identify the home damage equation (2).

This variable is considered a suitable instrument for six main reasons. First, previous Australian research by Nguyen and Mitrou (2024b), demonstrates that cyclones, particularly those of greater severity and closer proximity to homes, substantially increase self-reported weather-related home damage. Second, the suitability of this cyclone exposure-based instrument is supported by our data, as cyclones are explicitly cited as an example of a natural disaster causing home damage in the relevant questionnaire prompt. Third, the instrument is theoretically grounded: plausibly exogenous cyclone exposure may lead to home damage directly, preceding any potential effects on an individual's LoC. This likely sequence of impact strengthens the validity of our instrumental variable strategy, which assumes that the instrument affects individuals' LoC primarily through the channel of home damage.

Fourth, this instrument varies over time for the same individuals, facilitating its application in individual fixed-effects models, which effectively control for both time-invariant and time-variant individual unobservable factors. Fifth, similar instruments have been employed in previous Australian studies to investigate the causal impact of weather-related home damage on mental health (Baryshnikova & Pham 2019) or life satisfaction (Nguyen & Mitrou 2024a).[5]

Sixth, we will empirically assess the strength of this instrument by additionally controlling for several time-varying variables, including income and health, which may also be affected by cyclone exposure. Specifically, as noted above, our identification strategy relies on the key

[5] Particularly, Baryshnikova and Pham (2019) utilize a variable representing the occurrence of natural disasters within an individual's state or territory of residence during a given year as an instrument for weather-related home damage. In contrast, our instrument, which closely aligns with that employed by Nguyen and Mitrou (2024a), offers two key improvements over the approach of Baryshnikova and Pham (2019). First, our instrument is derived from exogenously measured meteorological factors, whereas their instrument relies on natural disaster measures influenced by human behaviours, potentially introducing bias into disaster estimates (Dell *et al.* 2014; Carleton & Hsiang 2016; Botzen *et al.* 2019). Second, our data and empirical model enable a more geographically granular instrument: ours is constructed at the postcode level (with over 3,000 postcodes in Australia), whereas theirs is based on the state level, encompassing only eight states and territories.

assumption that cyclone exposure influences individuals' LoC primarily through home damage. While this assumption is highly plausible for the reasons previously outlined, it is unlikely to be formally or conclusively tested. To address potential concerns regarding time-varying unobserved factors that may also be affected by cyclone exposure—particularly those likely to be influenced more immediately by the same event than LoC—it is prudent to control for as many relevant variables as possible (Wooldridge 2010).

Following the methodology outlined by Nguyen and Mitrou (2024b, 2025), we determine an individual's exposure to cyclones within a given year by considering both the distance to the cyclone's eye and its category. This is achieved by linking the HILDA data to a publicly available historical cyclone database from the Australian Bureau of Meteorology (BOM). We connect these datasets by aligning the cyclone path and timing from the historical cyclone database with the individual's residential postcode centroid and interview date from HILDA. We utilize the restricted-access version of the HILDA dataset, which requires a specialized application process and includes postcode-level data, offering the highest level of geographical granularity available (Summerfield *et al.* 2024).

In the baseline regressions, we adopt a single cyclone exposure measure indicating whether the individual's residential postcode was affected by any cyclone within a 100 km radius of the cyclone's eye in the year prior to the survey, using this as a cyclone exposure-based instrument. This approach is selected to maximize the number of individuals identified as affected by such cyclones and to establish a strong instrument, ensuring the reliability of our analysis. Appendix Table A1, which presents variable descriptions and summary statistics, shows that 760 individuals, accounting for approximately 1.4% of the sample, were affected by a cyclone within 100 km of their residential postcode centroid. This number of affected individuals is sufficient to capture the impact of cyclones on weather-related home damage (Wooldridge

2010). In robustness checks, we will employ alternative instruments constructed using the individual's exposure to cyclones with varying levels of severity.

We include a parsimonious number of individual and household-level time-variant variables in X_{it}. These variables encompass the individual's age (and its square), marital status, education, the number of household members, and major city residency. To address potential temporal differences in outcomes, we separately control for survey year and quarter dummies. Moreover, we account for regional differences by including state/territory dummies in both equations. Additionally, we control for variations in local socio-economic environments that may influence individual behaviors by incorporating regional unemployment rates and the relative socio-economic disadvantage index (SEIFA).

Utilizing multiple observations per individual, we employ an individual fixed-effects (FE) regression methodology in both equations. This analytical approach effectively mitigates concerns regarding individual heterogeneity, encompassing factors such as residential location preferences. The inclusion of individual fixed effects is imperative to account for unobservable time-invariant characteristics, a critical consideration given empirical evidence indicating that regions prone to natural disasters often exhibit greater levels of socioeconomic disadvantage (Dell *et al.* 2014; Botzen *et al.* 2019).

We employ an Ordinary Least Squares (OLS) method to estimate the individual fixed-effects equation (1) and conduct a two-stage least squares (2SLS) regression method for the fixed-effects instrumental variable (FE-IV) model. Since both the outcome and treatment variables are measured at the individual level, modelling the impact of home damage on LoC at this level is appropriate. Furthermore, we cluster robust standard errors at the individual level to account for potential serial correlation issues (Cameron & Miller 2015).

The estimates of β_1 from these empirical models capture the treatment effects of weather-related home damage on LoC at the mean. Departing from regression at the mean, our study explores quantile treatment effects, enabling an examination of how the treatment effect varies across different points of the LoC distribution (Koenker & Bassett 1978; Firpo *et al.* 2009). By analysing treatment effects at various quantiles, we gain insights into the differential impact of weather-related home damage on individuals, thereby informing the development of more targeted and efficacious policy interventions.

To estimate the quantile regression equation (1), we employ an unconditional quantile regression (UQR) method proposed by Firpo *et al.* (2009). This selection is preferred over the conditional quantile regression method developed by Koenker and Bassett (1978) as it provides a means to recover the marginal impact of explanatory variables on the unconditional quantile of Y without necessitating the rank-preserving condition (Firpo 2007; Firpo *et al.* 2009). Furthermore, to estimate the quantile IV regression equations (1) and (2), we utilize a recently developed quantile regression for panel data (QRPD) method by Powell (2020, 2022), which employs a Generalized Method of Moments (GMM) estimator to estimate treatment effects along the distribution of the outcome variable. Powell's method (2022) aligns with our research aims, as it accommodates both individual fixed effects and instrumental variable methods within a quantile fixed-effects instrumental variable (FE-IV) framework.

4. Results

4.1. Descriptive results

Table 1 unveils stark differences in key characteristics between individuals who reported weather-related home damage and those who did not. Specifically, 957 individuals, comprising 1.78% of the main analytic sample, reported experiencing weather-related home damage and constitute the "treated" group.[6] This sample size is sufficient to assess the potential impact of home damage on LoC. Compared to individuals who did not report weather-related home damage (the "control" group), treated individuals tend to be younger, less educated, and more likely to be born in Australia. They also face greater socio-economic challenges, residing in areas with lower socio-economic advantage. Notably, individuals who experienced home damage are significantly more likely to have been within 100 km of any cyclone's eye. This pattern aligns with the global trend that disadvantaged individuals and locations are more likely to encounter higher natural disaster risk (Dell *et al.* 2014; Botzen *et al.* 2019), highlighting the importance of accounting for individual fixed effects when analysing the impacts of natural disasters.

Furthermore, Table 1 reveals a noticeable disparity in LoC between the groups. Treated individuals report a significantly lower sense of control compared to their unaffected counterparts. This disparity is visually evident in Figure 1 – Panel A, which illustrates the distribution of LoC levels, where treated individuals are overrepresented at the lower end of the distribution. Similarly, Panel B of Figure 1, which depicts changes in individuals' LoC relative to the previous wave, shows that treated individuals are overrepresented at the negative end of the LoC change distribution, suggesting a decline in their perceived control.[7] However, as discussed in Section 3, this difference may not stem solely from weather-related home damage but rather reflect pre-existing factors influencing both home damage and LoC. The subsequent analysis directly addresses this critical issue.

[6] Among these 957 affected individuals, fewer than 70 reported multiple instances of home damage over the study period, with nearly all experiencing two occurrences. The limited number of individuals with multiple instances of home damage is insufficient for a robust separate analysis.

[7] Figure 1 displays the distribution of LoC for both the treated and control groups, demonstrating substantial variations in this outcome. These variations enable an examination of the differential impacts of home damage on individuals at different points of the LoC distribution. Moreover, Panel B of Figure 1, together with the substantial within-individual standard deviations in LoC reported in Appendix Table A1, confirms sufficient temporal variation in this measure to support the use of an individual FE regression model. It is important to note that, for demonstration purposes, we have intentionally used raw summary scores of LoC in this figure.

4.2. *Regression results*

Table 2 presents estimates of the home damage variable derived from four regression models at the mean: a pooled regression without controlling for individual fixed effects (reported in Column 1), an individual FE model (Column 2), an IV model without controlling for individual fixed effects (Columns 3 and 4), and an individual FE-IV model (Columns 5 and 6). The pooled regression results (Column 1) reveal a negative and statistically significant (at the 1% level) association between home damage and LoC. This negative correlation suggests that individuals whose homes were damaged or destroyed by a weather-related disaster report a lower sense of control over their lives. In contrast, the estimate of home damage obtained from the individual FE estimator, reported in Column 2 of Table 2, is not statistically significant, suggesting no discernible association between home damage and LoC in this specification.

The estimates from the two IV regression models at the mean unveil two notable findings. First, the estimates of the cyclone exposure variable from the first-stage regressions, reported in Columns 3 and 5, are positive and highly statistically significant at the 1% level. This suggests that individuals affected by any cyclone within 100 km of its eye are more likely to report weather-related home damage.[8] For instance, consistent with the findings by Nguyen and Mitrou (2024b), the estimate from the first stage of the FE-IV regression indicates that individuals affected by such a cyclone are about 10 percentage points more likely to report home damage (Column 5). Importantly, the first-stage F-statistic, reported at the bottom of Columns 3 and 5 in Table 2, surpasses 230 in both IV regressions, robustly rejecting the null hypothesis of a weak instrument (Stock & Yogo 2005). Second, the IV estimates of home damage are negative and statistically insignificant, regardless of whether individual fixed

[8] This estimated effect of cyclone exposure on home damage is highly statistically significant and substantial, accounting for about 12% of the sample mean (1.8%) of individuals reporting weather-related home damage. However, the estimate remains well below 100%, suggesting that not all individuals affected by a cyclone reported home damage. This could be due to the cyclone not being severe enough or because their homes were resilient to such an event. Additionally, as noted in the survey question prompt, other weather-related events, such as floods or bushfires, may have contributed to the reported home damage.

effects are accounted for. Therefore, the estimate derived from our preferred FE-IV model indicates a statistically insignificant treatment effect of weather-induced home damage on LoC at the mean of the LoC contribution.

As with the regressions at the mean presented in Table 2, Figure 2 similarly reports graphical estimates of the home damage variable across nine deciles from four quantile regression models: a pooled model without controlling for individual fixed effects (Panel A), an individual FE model (also in Panel A), an IV model without controlling for individual fixed effects (Panel B), and an individual FE-IV model (Panel B).[9]

The pooled quantile regression estimates (Panel A) are negative and statistically significant at the 1% level for quantiles at or below the 60th quantile. Moreover, these estimates are more pronounced at the lower end of the distribution. These results suggest that weather-related home damage is negatively associated with the LoC for individuals having a weaker sense of control, with the negative relationship being more pronounced for those at the lower end of the distribution. However, the quantile FE estimates, also reported in Panel A, show no statistically significant association between home damage and LoC, as all estimates are statistically insignificant across the entire distribution of LoC.

Panel B in Figure 2 presents the quantile IV regression results. The quantile IV estimates are consistently negative and statistically significant at the 1% level across all nine deciles of the LoC distribution. However, the magnitude of the effect varies. The estimates are relatively small at the upper end of the distribution (70th, 80th and 90th quantiles) but begin to increase

[9] In our analysis, we employ the qregpd command developed by Powell (2022) in STATA MP Version 18 to conduct estimations using a quantile instrumental variable model, regardless of whether individual fixed effects are accounted for. The qregpd command utilizes a GMM estimator, as described by Wooldridge (2010) and Powell (2022), for estimating these equations. It is important to note that while qregpd incorporates the instrument, it does not provide any test statistic for evaluating the strength of the instrument.

in absolute value from the 60th quantile, reaching a maximum negative impact at the 10th quantile.

The quantile FE-IV estimates, also reported in Panel B of Figure 2, exhibit a slightly different pattern compared to the quantile IV estimates, particularly for individuals at the median of the distribution. Similar to the quantile IV estimates, the FE-IV estimates are consistently negative and statistically significant at the 1% level across all nine deciles of the LoC distribution, except at the median, where the estimate is statistically significant at the 10% level and smallest in absolute magnitude. Furthermore, the quantile FE-IV estimates are relatively small at the upper end of the distribution (70th and 90th quantiles) but increase in absolute value from the 60th quantile, reaching their maximum negative impact at the 10th quantile. Numerically, weather-related home damage reduces the LoC of individuals at the upper end of the distribution (70th and 90th quantiles) by only 0.08 standard deviations (SD). In contrast, it diminishes the LoC of individuals at the 10th quantile by 0.28 SD, which is more than three times the effect observed for those at the higher end of the distribution (≈-0.28/-0.08).

In summary, our preferred quantile FE-IV regression results demonstrate that weather-related home damage significantly reduces individuals' LoC. Furthermore, individuals at the lower end of the LoC distribution experience the most pronounced decline in their LoC following weather-related home damage.

5. Robustness checks and additional results

5.1. Robustness checks

We assess the robustness of our findings through a series of specification tests. We first examine the robustness of our findings by employing alternative methods for constructing aggregate LoC scores. In the baseline analysis, we follow standard practice in the literature by computing the summary LoC score as the simple sum of individual responses to the seven survey questions (Cobb-Clark & Schurer 2013; Elkins *et al.* 2017; Nguyen *et al.* 2024b). This approach assumes a linear relationship between the individual measures and overall LoC. In this section, we consider two alternative aggregation methods. The first computes the LoC score by summing the squared values of individual responses, while the second derives the score by taking the maximum response across the seven categories.

The results, presented in Panels B1 and B2 of Appendix Table A3, indicate that our main finding—a statistically insignificant effect of home damage on LoC at the mean—remains robust under these alternative aggregation methods.[10] Additionally, the FE-IV quantile regression results in Panel B1, while differing slightly in magnitude from the baseline regression results (re-reported in Panel A), suggest that each response category captures a distinct aspect of LoC. Nevertheless, they confirm our primary conclusion that the negative impact of home damage is more pronounced at the lower end of the LoC distribution.

We next investigate the sensitivity of our findings using different instruments. Specifically, we separately employ two alternative instruments, each constructed from a different cyclone exposure measure derived from the baseline instrument. The two cyclone exposure-based instruments are: exposure to any cyclone within 40 km of its eye, and exposure to a category 5 cyclone within 100 km of its eye.[11] The results from these sensitivity tests are presented in Panels C1 and C2, respectively, and reveal two notable findings.

First, utilizing exposure to more severe cyclones, as measured by closer proximity to the home or higher category, enhances the strength of the instrument, as indicated by a higher reported F statistic compared to the baseline. This finding is consistent with the previous Australian study by Nguyen and Mitrou (2024b), which observes that the impact of cyclone exposure on

[10] As with the original LoC measure, we standardize these two alternative measures. However, we refrain from conducting a quantile FE-IV regression for the second measure due to insufficient variation (i.e., the raw scores range only from 1 to 7), which limits the feasibility of a robust quantile analysis.

[11] We refrain from utilizing other cyclone exposures as instruments due to their limited capacity to induce home damage or the relatively small number of individuals affected by such cyclones during the study period, thus rendering them weak instruments.

home damage increases with the cyclone category and decreases with the distance from the cyclone eye.

Second, using exposure to more severe cyclones as an instrument tends to amplify the estimated effects of weather-related home damage, both in terms of statistical significance and magnitude. For example, compared to the baseline estimate at the mean reported in Panel A, Column 1, employing exposure to a cyclone within 40 km as an instrument yields an estimated effect of home damage that is approximately three times larger in absolute magnitude (i.e., ≈-0.48/-0.16) and statistically significant at the 10% level (Panel C1 - Column 1). Furthermore, this approach results in a more pronounced estimated effect of weather-related home damage at the two lowest deciles of the LoC distribution (Panels C1 and C2 - Columns 2 and 3). The stronger estimated impacts associated with exposure to more severe cyclones align with the expectation that such cyclones cause greater home damage (BOM 2024), thereby exerting a more substantial influence on LoC, particularly among individuals at the lower end of the LoC distribution.

We next exclude certain time-variant variables, such as education, marital status, household size, and whether the individual lived in a major city, which may be concurrently affected by the cyclone exposure-based instrument, from the regression. The results, presented in Panel 1 of Appendix Table A3, indicate that weather-related home damage now has a significantly stronger impact on LoC, particularly for individuals at the median or lower quantiles of the distribution, than previously observed in the baseline regressions. For example, for individuals at the 10th quantile, weather-related home damage now reduces their LoC by 0.55 SD, which is about 2 times greater than the baseline estimate of 0.28 SD. However, consistent with the baseline results, this robustness check confirms that individuals at the lowest quantiles of the LoC distribution exhibit the most significant reduction in their LoC.

Conversely, we separately and additionally control for each of several time-variant variables that may be concurrently correlated with natural disaster-related home damage in the regression (Baryshnikova & Pham 2019; Johar *et al.* 2022). Specifically, we first control individually for each of four income-related variables: equivalised household disposable income, individual regular market income, non-wage irregular income, and Australian Government non-income support payments.[12] The results of these analyses are reported in Panels D2 to D5 of Appendix Table A3. These findings indicate that the inclusion of these income-related controls does not alter our main result regarding the disproportionately pronounced diminishing effect of weather-related home damage on individuals at the lower end of the LoC distribution. Notably, the inclusion of the first three income-related variables yields an even more pronounced estimated effect for individuals at or below the median of the LoC distribution (see Panels D2 to D4). The robustness of our main finding to the inclusion of these controls is consistent with the statistically insignificant association between weather-related home damage and financial outcomes reported by Johar *et al.* (2022).

Similarly, including general health, as measured by the Short Form (SF)-36 general health summary score, as a control in the regression slightly decreases the absolute magnitude of the estimates across nearly all points of the LoC distribution (i.e., the estimates become less negative, as shown in Panel D6). However, this adjustment reaffirms the key finding that the impact of home damage is more pronounced among individuals at the lower end of the LoC distribution. Overall, these robustness checks address the concern that unobservable, time-variant individual factors may be correlated with both LoC and home damage, thereby further supporting the validity of our key assumption that cyclone exposure affects LoC primarily through the home damage channel.

[12] All income-related variables are reported by financial year, denominated in thousands of dollars, and adjusted for inflation using the Consumer Price Index (CPI), with 2010 as the base year.

5.2. Profiling the compliers

This study employs an IV approach to examine the causal impact, meaning the IV estimates in this paper measure the local average treatment effect (LATE) of weather-related home damage on an individual's LoC (Imbens & Angrist 1994). Specifically, the LATE applies to individuals whose homes were damaged due to cyclone exposure. Understanding the characteristics of compliers is therefore valuable. To investigate this, we apply the method proposed by Marbach & Hangartner (2020) to compare the characteristics of compliers and noncompliers.[13] Figure 3 presents the variable means for the full estimation sample, as well as the sample shares and variable means for compliers, never-takers, and always-takers across five selected socio-demographic variables. Approximately 11% of individuals in our estimation sample are compliers, 87% are always-takers, and 2% are never-takers. Compared to always-takers and never-takers, compliers tend to come from higher socio-economic backgrounds, as evidenced by their greater likelihood of being older, having higher qualifications, and residing in owned homes or higher-income households.

The findings from our IV approach, while primarily applicable to individuals who explicitly reported home damage due to cyclone exposure, have potentially significant implications given the global prevalence of cyclones and the increasing risks associated with their escalating intensity (Emanuel 2005; Webster *et al.* 2005; Hsiang & Jina 2014).[14] Furthermore, our findings contribute novel evidence on the broader impact of cyclones, particularly their role in

[13] As detailed in Section 6, for time-variant variables (excluding individual age), subgroup identification is based on their first appearance in the sample. This approach mitigates concerns that cyclone exposure may influence these variables.

[14] Similar to other Australian and international studies examining the causal impacts of cyclone exposure (Currie & Rossin-Slater 2013; Franklin & Labonne 2019; Groen *et al.* 2020; Deryugina & Marx 2021; Nguyen & Mitrou 2025), this study identifies cyclone exposure based on maximum wind speed. While this approach aligns with data availability constraints, it does not distinguish the effects of cyclones from those of co-occurring hazards, such as torrential rain, flooding, and storm surges. This limitation arises because, although this study utilizes the most detailed geographic identifier available in HILDA, the dataset lacks the spatial precision required for a rigorous evaluation of other natural disasters. Conducting such an analysis would necessitate more granular spatial data, such as geocoded household locations. Consequently, a comprehensive assessment of the distinct impacts of these hazards remains a direction for future research.

diminishing individuals' sense of control over their life outcomes (Carleton & Hsiang 2016; Botzen *et al.* 2019; Young & Hsiang 2024). This insight is particularly significant, as most prior studies have treated LoC as a fixed trait, while an expanding body of evidence highlights the role of internal LoC in fostering positive socio-economic outcomes (Nguyen *et al.* 2024b).

5.3. Additional results

This subsection provides additional results on the impacts of cyclone exposure on individuals' LoC. Following the methodology outlined by Nguyen and Mitrou (2025), we investigate the effects of cyclone exposure by incorporating a variable describing the individual's exposure to local cyclones as an additional explanatory variable in an individual fixed effects model similar to Equation (1). Specifically, we use this cyclone exposure variable in place of the weather-related home damage variable in Equation (1), while other explanatory variables remain the same as previously described in Section 3. For brevity and demonstration purposes, we separately employ one of four cyclone exposure measures, each identified by (i) the distance from the individual's residing postcode centroid to the cyclone eye (i.e., 40 km or 100 km) and (ii) the cyclone category (i.e., any category and category 5 only). Similar to the analysis of weather-related home damage, we employ an individual fixed effects regression model to explore the effects of cyclone exposure on LoC both at the mean and along the distribution of LoC. This section utilizes a larger sample than previously used, as we only need to restrict the sample to HILDA survey waves with valid LoC measures (recall that previously we restricted the sample to survey waves with both home damage and LoC measures available).

The results from this experiment, presented in Appendix Table A4, show limited evidence that exposure to cyclones substantially influences individuals' LoC. This holds for both regressions at the mean and across the LoC distribution, as the estimated effects of cyclone exposure measures, while negative in most cases, are not statistically significant.[15] However, one notable exception is observed: exposure to a cyclone within 40 km of its eye significantly reduces LoC for individuals at the 80th quantile of the LoC distribution by 0.16 SD, with statistical significance at the 5% level (Panel A, Column 8).

The widespread statistically insignificant impact of cyclone exposure, compared with the widespread statistically significant impact of weather-related home damage, suggests that while LoC is resilient to cyclone exposure, only cyclones that damage or destroy homes diminish individuals' perception of control over their life outcomes. Moreover, as discussed above, the absence of a statistically significant effect of "indirect" cyclone exposure, in contrast to the highly significant impact identified using the quantile FE-IV estimator, may be attributed to the instrumental variable approach capturing only the effect among treated individuals—those who reported home damage due to cyclone exposure (Imbens & Angrist 1994). In this regard, our findings are consistent with Nguyen and Mitrou (2024a), who demonstrated that weather-related home damage has a greater negative impact on life satisfaction than cyclone exposure alone.

6. Heterogeneity

To explore potential channels through which home damage affects LoC and to identify vulnerable sub-populations, we employ a quantile FE-IV regression model[16] to estimate the

[15] As demonstrated in robustness section 5.1, to address the concern regarding the potential confounding effects of other time-variant variables that may be concurrently correlated with both cyclone exposure and LoC, we have conducted additional experiments by separately controlling for individual income and health variables in the individual FE regression model. The unreported results show minimal sensitivity in our findings. Furthermore, as presented in heterogeneity section 6, we have conducted separate FE regressions for two income subgroups (lower income vs. higher income households, defined relative to the median) to explore the potential mediating or exaggerating role of income on LoC. However, our data do not provide evidence to support such a role, as the estimates for both subgroups are mostly statistically insignificant.

[16] We conducted a similar heterogeneous analysis of the impact of home damage on the mean locus of control by applying the FE-IV model to various subgroups, as described below. Consistent with the population estimates from the FE-IV regression at the mean, all subgroup estimates of home damage are negative and statistically insignificant (see Appendix Table A5 – Column 1). Moreover, the results in Appendix Table A5 confirm the empirical strength of the instrument, as the F-statistic from the first-stage regression exceeds 70 in all cases.

effects of home damage separately for two distinct groups defined by four individual or household characteristics. These characteristics include gender (male vs. female), age group (young vs. old, categorized relative to the median population age), homeownership status (renters vs. homeowners) and income group (lower income vs. higher income households, defined relative to the median). These characteristics were selected based on prior studies suggesting that changes in LoC in response to major life events may vary by gender or age (Cobb-Clark & Schurer 2013; Elkins *et al.* 2017; Nguyen *et al.* 2024b) and 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).[17] To mitigate concerns regarding the influence of weather-related home damage on sub-population classification, individuals are categorized based on the values of time-variant variables (excluding age) observed at their first appearance in the sample.

Figure 4 presents the heterogeneous results across four panels, with each panel displaying subgroup estimates based on one of the characteristics described above. Panel A of Figure 4 presents subgroup estimates by gender, revealing minimal gender differences in the impact of weather-related home damage on LoC. Consistent with the pooled regression results, the estimated effects are more pronounced for individuals at the lower end of the LoC distribution. However, these effects do not differ noticeably between males and females at any point along the LoC distribution.

Panel B of Figure 4 represents subgroup estimates by age, indicating that natural disaster-induced home damage disproportionately reduces LoC of older individuals compared to younger ones. Specifically, the estimated effects of home damage are more negative or statistically significant for older individuals across all deciles, except at the 20th quantile,

[17] We do not conduct a heterogeneous analysis based on other characteristics due to the lack of a strong theoretical or empirical rationale or insufficient statistical power resulting from a small sample size or a weak instrument.

where the estimates are similar between the two groups, and at the 90th quantile, where the effect is more negative for the younger group. The difference between the two age groups is statistically significant, at least at the 5% level, across the 10th, 30th, 40th, 60th and 70th quantiles, as evidenced by non-overlapping 95% confidence intervals. Moreover, consistent with the results for the entire population, subgroup estimates also reveal that home damage has a more pronounced impact on individuals positioned at the lower end of the spectrum, particularly among older individuals.

Subgroup estimates by homeownership status, reported in Panel C, suggest that weather-related home damage disproportionately reduces LoC of renters. Specifically, with the exception of the 30th quantile, where homeowners are more negatively affected, the estimated effects of home damage are more negative and statistically significant for renters at the 20th, 40th, 50th, 60th, 70th, and 90th quantiles. Moreover, the difference between homeownership groups is statistically significant at the 5% level for all quantiles except the 20th and 70th. However, no discernible differences are observed between homeowners and renters at the remaining quantiles (i.e., 10th and 80th), as the estimates for both groups are largely similar.

Panel D of Figure 4 illustrates a notable disparity in the impact of home damage on LoC across income groups, with this effect varying along the LoC distribution. Specifically, the estimated effects of home damage are more negative and statistically significant for lower-income individuals across the six lowest deciles, except at the 30th quantile, where the estimates are similar between the two groups. Moreover, the difference between income groups is statistically significant at the 5% level for the 10th, 40th, and 70th quantiles, as indicated by non-overlapping 95% confidence intervals. By contrast, home damage has a more negative and statistically significant effect on individuals from higher-income households in the top three deciles, with the difference reaching statistical significance at the 90th quantile. However, consistent with the pooled regression results, subgroup estimates confirm that home damage has a more pronounced impact on individuals at the lower end of the LoC spectrum, regardless of income group.

Overall, the heterogeneous analysis highlights substantial differences in the impact of weather-related home damage on LoC across various socio-demographic groups, while finding no significant gender heterogeneity. While the extent of this heterogeneity varies along the LoC distribution, a key finding is that certain individuals—older adults, renters, and those from lower-income households—experience more pronounced negative effects. These groups are typically more financially disadvantaged, as suggested by their demographic characteristics. Moreover, the mean LoC figures by subpopulation reported in Appendix Table A5 indicate that these individuals also have lower LoC scores than their counterparts, suggesting they are not only economically disadvantaged but also more psychologically vulnerable.

These subgroup differences, combined with our main finding that the most severe impact of weather-related home damage on LoC occurs among individuals at the lower end of the internal LoC distribution, suggest that economically and psychologically vulnerable groups are disproportionately affected. In this regard, our findings align with the broader literature, which shows that disadvantaged individuals typically suffer greater adverse consequences from natural disasters (Dell *et al.* 2014; Carleton & Hsiang 2016). Collectively, these results highlight the need for targeted support policies to enhance resilience and provide assistance to these vulnerable populations.

7. Conclusion

This study represents the first investigation into the causal impacts of natural disaster-driven home damage on individuals' locus of control. Utilizing longitudinal data from the Household, Income and Labour Dynamics in Australia survey, we implemented an individual fixed effects instrumental variables (FE-IV) approach. This method leverages time-varying, exogenous exposure to local cyclones to effectively address the endogeneity of self-reported weather-related home damage. This study unveils new and robust evidence that natural disaster-induced home damage substantially reduces individuals' sense of control over their life outcomes. However, this significant impact is only observed in the quantile FE-IV regressions, where individuals near or below the median of the LoC distribution experience the most pronounced negative impact of weather-related home damage. Notably, those at the lowest end of the distribution exhibit the greatest decline, with weather-related home damage reducing their LoC by 0.28 standard deviations.

Our heterogeneous analysis further reveals substantial differential impacts of weather-related home damage on LoC across various socio-demographic groups. The extent of this heterogeneity varies along the LoC distribution, with a general trend indicating more pronounced impacts for older individuals, renters, and those from lower-income households.

The results presented in this study have significant methodological and policy implications. Methodologically, our findings highlight the importance of adequately addressing the endogeneity of self-reported natural disaster-related home damage when quantifying its impacts on locus of control. Specifically, we address this endogeneity by leveraging time-varying, exogenous exposure to local cyclones in our FE-IV approach. This study also demonstrates the benefits of examining the effects of natural disaster exposure beyond the mean of the LoC distribution. Specifically, our results show that focusing solely on the mean impact would inadvertently fail to detect the severe consequences of natural disaster exposure on individuals' LoC and miss crucial insights into the differential impacts across different points of the distribution.

Our novel finding of the negative and substantial impacts of weather-related home damage on internal LoC indicates that LoC can be altered under specific conditions. This new evidence on the malleability of LoC is particularly important, as most prior studies globally have treated LoC as a fixed trait. From a policy perspective, this insight provides valuable guidance for the development of effective policies and interventions aimed at supporting affected populations, particularly those who are economically disadvantaged and more psychologically vulnerable at baseline, as demonstrated in this paper to be disproportionately impacted by natural disasters. Such policies are critical, especially considering the well-established role of internal LoC in promoting positive socio-economic outcomes and the growing frequency of extreme weather events.

This study provides robust and novel evidence on the causal impact of weather-related home damage on locus of control. However, several limitations must be acknowledged, which also present opportunities for future research. First, the constraints of the available data and identification strategy prevent a robust analysis of the effects of other natural disasters, such as floods or storm surges. Future research utilizing alternative datasets or methodologies could expand the pool of compliers in an instrumental variable approach and deepen our understanding of how these events influence locus of control. Second, examining the broader impact of cyclones on other life outcomes—using the identification strategy applied in this study—would offer deeper insights into the social and economic consequences of natural disasters. Such research could inform the development of more effective policies aimed at mitigating the adverse effects of extreme weather events.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Table 1: Sample means of key variables by weather-related home damage status

	With home damage	Without home damage	With - Without (1) - (2)
	(1)	(2)	(3)
Age (years)	45.727	47.046	-1.319**
Male	0.481	0.464	0.017
ESB immigrant	0.076	0.095	-0.019**
NESB immigrant	0.086	0.113	-0.027***
Married/De facto [(a)]	0.675	0.658	0.017
Separated/divorced/widowed [(a)]	0.131	0.133	-0.002
Year 12 [(a)]	0.139	0.149	-0.010
Vocational or Training qualification [(a)]	0.433	0.391	0.041***
Bachelor or higher [(a)]	0.163	0.220	-0.057***
Household size	2.835	2.821	0.014
Major city [(a)]	5.044	4.903	0.142***
Local area unemployment rate (%)	4.925	5.549	-0.624***
Local area SEIFA index	0.471	0.624	-0.153***
Exposure to any cyclone within 100 km [(a)]	0.096	0.013	0.083***
Locus of control (standardized)	-0.123	0.031	-0.154***
Observations	957	52,821	

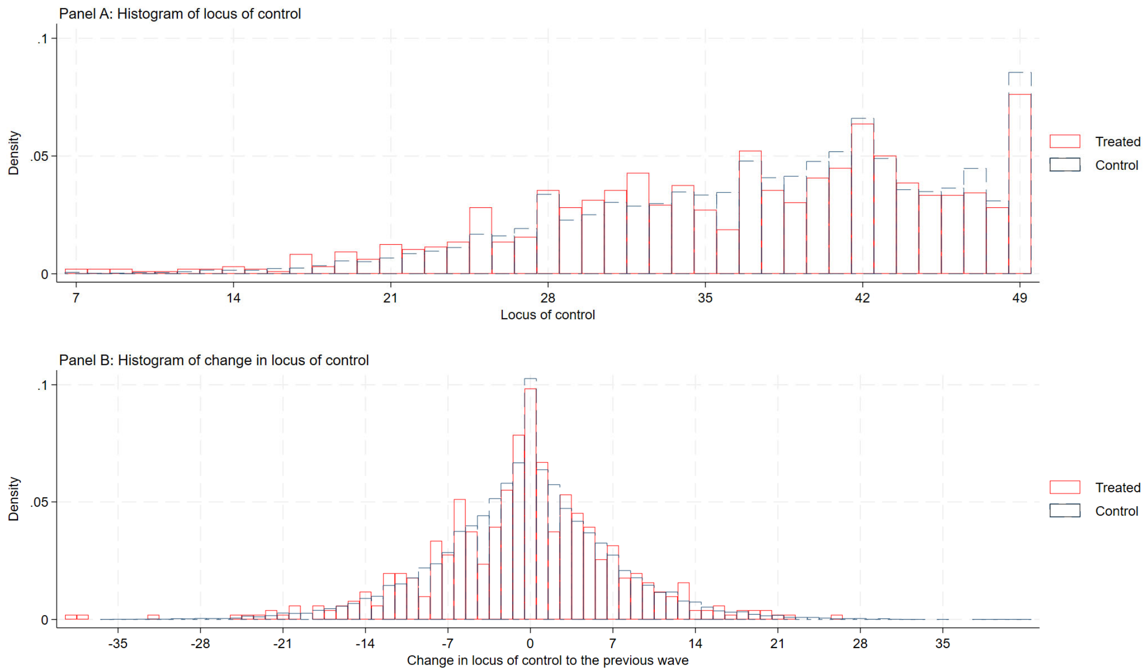
Notes: Figures are sample means. The 'treated group' consists of individuals with self-reported weather-related home damage in the past year, while the 'control group' includes those with no reported damage. [(a)] indicates a binary variable. Tests are performed on the significance of the difference between the sample mean for treated and control groups. The symbol *denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 2: Estimates of weather-related home damage on locus of control at the mean

Specification:	Pooled	FE	IV		FE-IV	
			First stage	Second stage	First stage	Second stage
	(1)	(2)	(3)	(4)	(5)	(6)
Home damage	-0.15***	-0.01		-0.66		-0.16
	[0.04]	[0.03]		[0.42]		[0.36]
Age	-0.01***	-0.01***	-0.01	-0.01***	-0.59***	-0.01***
	[0.00]	[0.00]	[0.02]	[0.00]	[0.08]	[0.00]
Age squared	0.00**	0.00**	-0.00	0.00**	0.00***	0.00**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Male	0.03***		0.12	0.03***		
	[0.01]		[0.12]	[0.01]		
Born overseas in ESB country [(a)]	0.05**		-0.35*	0.05**		
	[0.02]		[0.19]	[0.02]		
Born overseas in NESB country [(a)]	-0.20***		-0.14	-0.20***		
	[0.02]		[0.18]	[0.02]		
Married [(b)]	0.22***	0.05***	0.30	0.22***	0.97***	0.05***
	[0.02]	[0.02]	[0.19]	[0.02]	[0.37]	[0.02]
Separated [(b)]	0.04	-0.01	0.25	0.04	0.47	-0.01
	[0.03]	[0.03]	[0.25]	[0.03]	[0.57]	[0.03]
Year 12 [(c)]	0.10***	0.06**	-0.20	0.09***	-0.33	0.06**
	[0.02]	[0.03]	[0.21]	[0.02]	[0.46]	[0.03]
Vocational or training qualification [(c)]	0.13***	0.08**	0.14	0.13***	-0.49	0.08**
	[0.02]	[0.03]	[0.17]	[0.02]	[0.62]	[0.03]
Bachelor degree or higher [(c)]	0.21***	0.07**	-0.19	0.21***	-0.31	0.07**
	[0.02]	[0.03]	[0.19]	[0.02]	[0.64]	[0.03]
Household size	-0.02***	-0.03***	-0.04	-0.02***	-0.01	-0.03***
	[0.00]	[0.00]	[0.05]	[0.00]	[0.08]	[0.00]
Local area unemployment rate	0.00	-0.00	0.14	0.00	0.16	-0.00
	[0.01]	[0.01]	[0.10]	[0.01]	[0.11]	[0.01]
Local area SEIFA index	0.04***	0.00	-0.05**	0.04***	-0.03	0.00
	[0.00]	[0.00]	[0.02]	[0.00]	[0.06]	[0.00]
Major city	-0.06***	-0.04*	-0.65***	-0.07***	-0.96**	-0.04*
	[0.01]	[0.02]	[0.15]	[0.02]	[0.39]	[0.02]
Exposure to any cyclone within 100 km			10.44***		9.98***	
			[1.29]		[1.32]	
Observations	53,778					
Number of unique individuals	16,687					
Mean of dep. variable	0.03					
F test statistic			384.83		236.21	

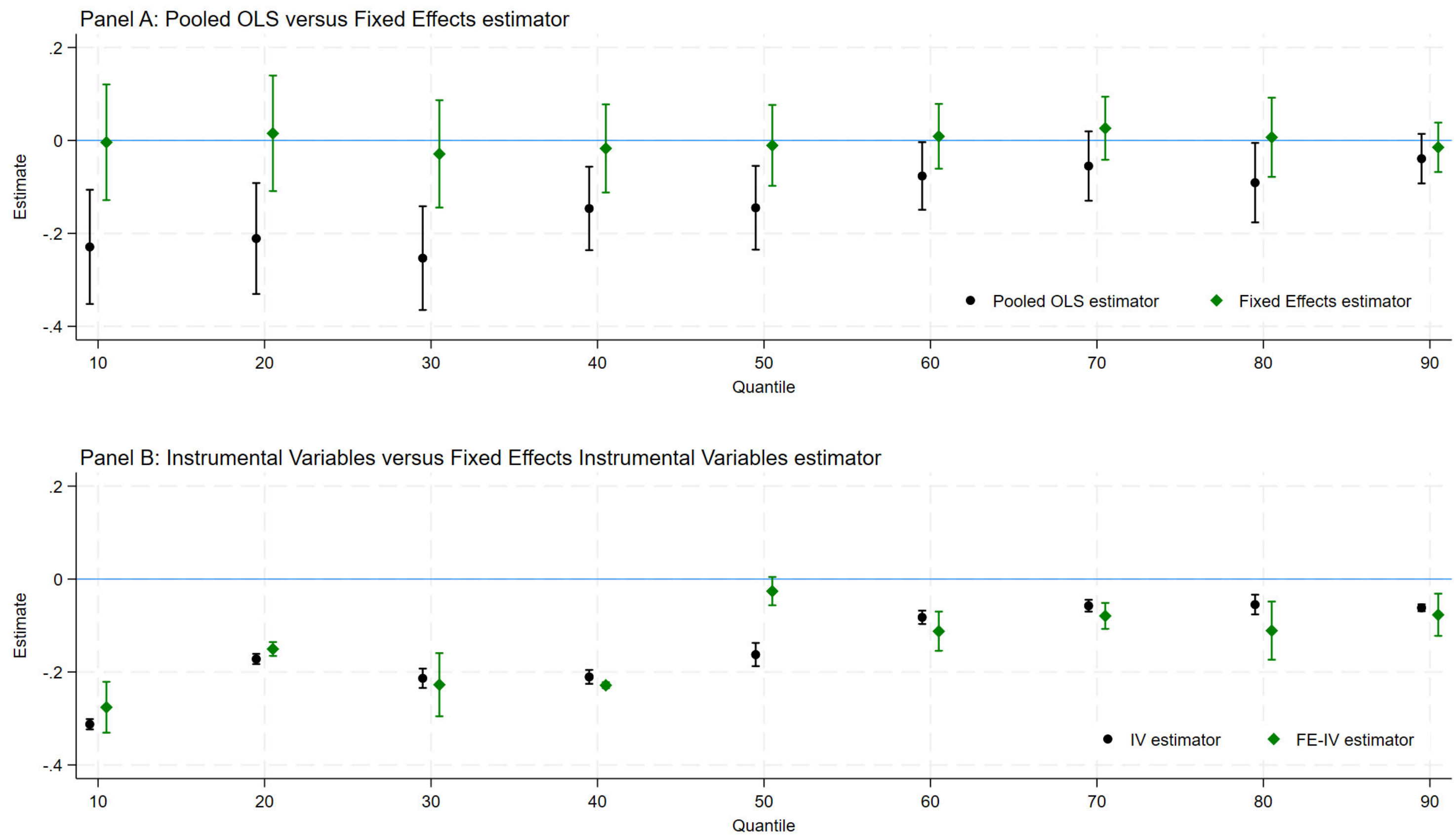
Notes: "Pooled" ("FE") results are from the regression (1) without (with) controlling for individual FEs. "IV" ("FE-IV") results from instrumental variable regressions (i.e., equations (1) and (2)) without (with) controlling for individual FEs. "F test statistic" denotes the F statistic for the strength of the excluded instrument in the first stage regression. [(a)], [(b)] and [(c)] indicates "Australia born", "Single" and "Under year 12 qualification" as the comparison group, respectively. Other explanatory variables include local area socio-economic variables, state/territory dummies, wave dummies, and survey quarter dummies. Robust standard errors clustered at the individual level in parentheses. Results from the first stage regressions are multiplied by 100 for aesthetic purposes. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 1: Histogram of locus of control by weather-related home damage status



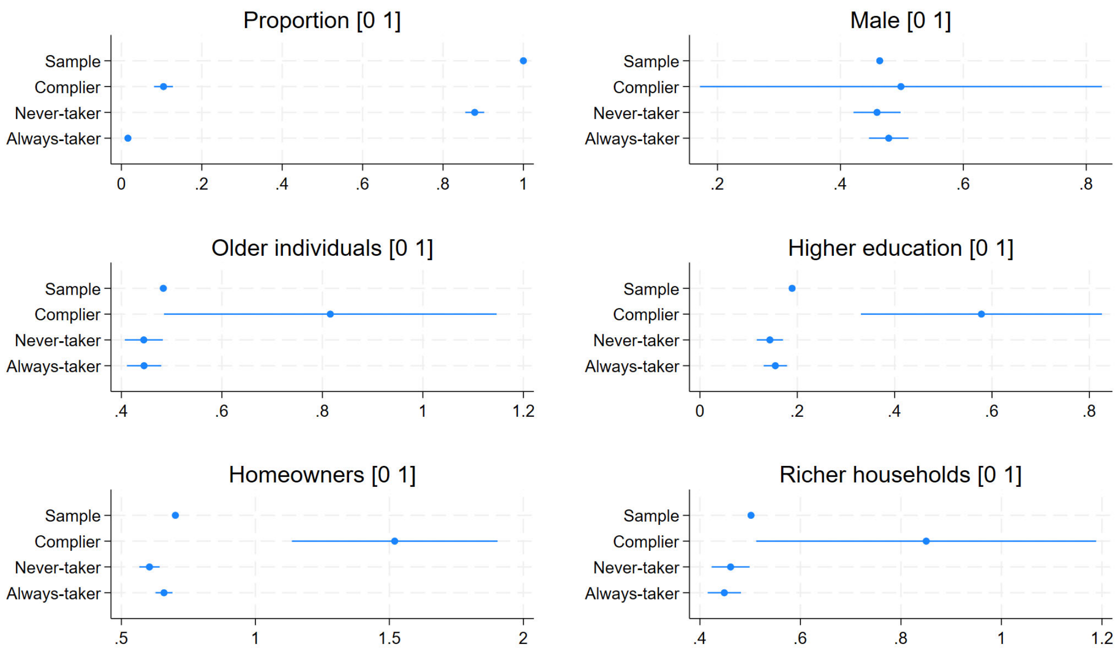
Notes: The "treated" group consists of individuals with self-reported weather-related home damage in the past year, while the "control" group includes those without home damage. Sample size: 53,778 observations in the final sample.

Figure 2: Estimates of weather-related home damage on locus of control along the distribution - Results from various estimators



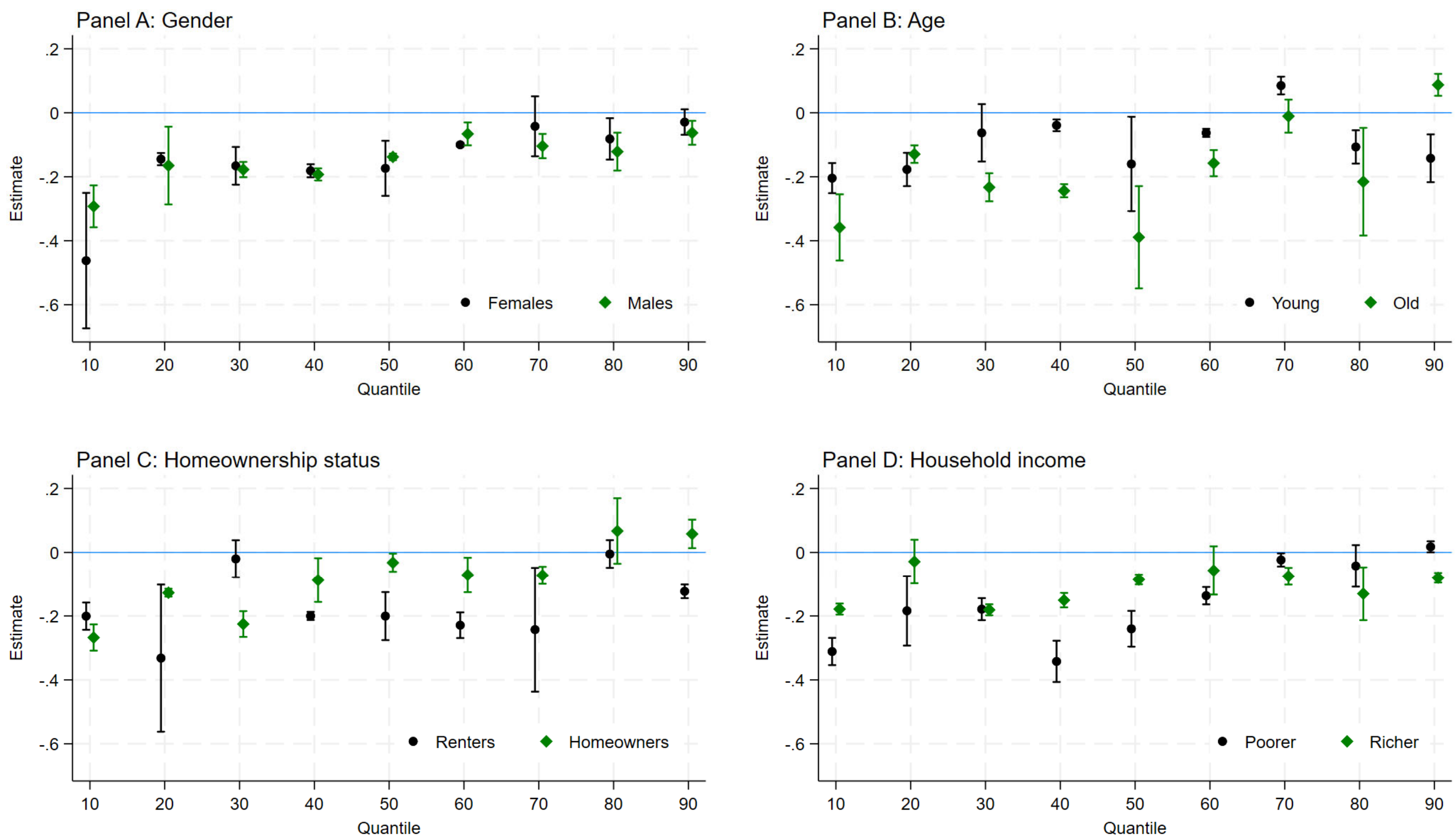
Notes: Results (estimates and their corresponding 95% confidence intervals) reported in each quantile and panel are from a separate regression. "Pooled OLS" and "Fixed Effect" estimators refer to the quintile regression Equation (1) without and with controlling for individual fixed effects, respectively. "Instrumental Variables" and "Fixed Effect Instrumental Variables" estimators refer to the quantile regression of Equations (1) and (2) without and with controlling for individual fixed effects, respectively. Instrument: Exposure to any cyclone within 100 km. Other explanatory variables include age (and its square), marital status, education, household size, urban, local area socio-economic variables, state/territory dummies, wave dummies, and survey quarter dummies. Gender and migration status variables are also included in pooled OLS and IV regressions. Standard errors in parentheses are obtained from bootstrapping (200 iterations) for Panel A and adjusted for clustering at individual level in Panel B. Results are reported in Appendix Table A2.

Figure 3: Descriptive statistics for the complier and noncomplier subpopulations



Notes: This figure reports descriptive statistics (mean and 95% bootstrap confidence intervals, from 1000 replications) for the complier and noncomplier subpopulations, using an estimator developed by Marbach & Hangartner (2020).

Figure 4: Heterogenous impacts of weather-related home damage on locus of control along the distribution



Notes: Results (estimates and their corresponding 95% confidence intervals) reported in each subgroup and quantile are from a separate quantile FE-IV regression. Instrument: Exposure to any cyclone within 100 km. Other explanatory variables include age (and its square), marital status, education, household size, state/territory dummies, year dummies, and survey quarter dummies. 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		
					Overall	Between	Within
Age	The respondent's age at the survey time (years)	47.023	15.00	100.00	18.49	18.58	4.02
Male	Dummy variable: = 1 if the individual is male and zero otherwise	0.464	0.00	1.00	0.50	0.50	0.00
Born overseas in ESB country	Dummy variable: = 1 if the individual was born overseas in an English-Speaking Background (ESB) country and zero otherwise	0.095	0.00	1.00	0.29	0.29	0.00
Born overseas in NESB country	Dummy variable: = 1 if the individual was born overseas in a Non-English-Speaking Background (NESB) country and zero otherwise	0.112	0.00	1.00	0.32	0.32	0.00
Married/De facto	Dummy variable: = 1 if the individual is married or in de factor relationship at the survey time and zero otherwise	0.659	0.00	1.00	0.47	0.43	0.22
Separated/divorced/widowed	Dummy variable: = 1 if the individual is separated/divorced/widowed at the survey time and zero otherwise	0.133	0.00	1.00	0.34	0.31	0.14
Year 12	Dummy: = 1 if the individual completes Year 12 and zero otherwise	0.149	0.00	1.00	0.36	0.32	0.16
Vocational or training qualification	Dummy: = 1 if the individual has a vocational or training qualification and zero otherwise	0.392	0.00	1.00	0.49	0.46	0.14
Bachelor degree or higher	Dummy: = 1 if the individual has a bachelor degree or higher and zero otherwise	0.219	0.00	1.00	0.41	0.39	0.13
Household size	Number of household members	2.821	1.00	13.00	1.43	1.24	0.74
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	4.905	2.70	7.90	1.06	0.58	0.91
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area	5.538	1.00	10.00	2.85	2.63	1.13
Major city	Dummy variable: = 1 if the individual lives in a major city and zero otherwise	0.621	0.00	1.00	0.49	0.46	0.17
Exposure to any cyclone within 100 km	Dummy variable: = 1 if an individual's residential postcode was within 100 km of any cyclone eye last year and zero otherwise	0.014	0.00	1.00	0.12	0.08	0.09
Locus of control	Summary scores from responses to seven questions asking about the individual's locus of control, standardized, with a higher score indicating a greater sense of control over life outcomes	0.028	-3.82	1.42	1.01	0.84	0.57
Home damage	Dummy variable: = 1 if home destroyed or damaged due to a weather-related disaster last year and zero otherwise	0.018	0.00	1.00	0.13	0.08	0.11

Notes: Statistics are calculated from the baseline sample of 53,778 individual-wave observations from 16,687 unique individuals.

Appendix Table A2: Estimates of weather-related home damage on locus of control along the distribution - Results from various estimators

	Q10th	Q20th	Q30th	Q40th	Q50th	Q60th	Q70th	Q80th	Q90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Pooled OLS regression model (Observations: 53,778, Individuals: 16,687)									
Home damage	-0.23***	-0.21***	-0.25***	-0.15***	-0.14***	-0.08**	-0.06	-0.09**	-0.04
	[0.06]	[0.06]	[0.06]	[0.05]	[0.05]	[0.04]	[0.04]	[0.04]	[0.03]
Panel B: Fixed effects regression model (Observations: 53,778, Individuals: 16,687)									
Home damage	-0.00	0.02	-0.03	-0.02	-0.01	0.01	0.03	0.01	-0.01
	[0.06]	[0.06]	[0.06]	[0.05]	[0.04]	[0.04]	[0.03]	[0.04]	[0.03]
Panel C: Instrumental variable regression model (Observations: 53,778, Individuals: 16,687)									
Home damage	-0.31***	-0.17***	-0.21***	-0.21***	-0.16***	-0.08***	-0.06***	-0.05***	-0.06***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]
Panel D: Fixed effects Instrumental variable regression model (Observations: 53,778, Individuals: 16,687)									
Home damage	-0.28***	-0.15***	-0.23***	-0.23***	-0.03*	-0.11***	-0.08***	-0.11***	-0.08***
	[0.03]	[0.01]	[0.03]	[0.00]	[0.02]	[0.02]	[0.01]	[0.03]	[0.02]

Notes: Results reported in each column and panel are from a separate regression. "Pooled OLS" and "Fixed Effect" estimators refer to the quintile regression Equation (1) without and with controlling for individual fixed effects, respectively. "Instrumental Variables" and "Fixed Effect Instrumental Variables" estimators refer to the quantile regression of Equations (1) and (2) without and with controlling for individual fixed effects, respectively. Instrument: Exposure to any cyclone within 100 km. "Observations" and "Individuals" refer to "Number of observations" and "Number of unique individuals", respectively. Other explanatory variables include age (and its square), marital status, education, household size, urban, local area socio-economic variables, state/territory dummies, wave dummies, and survey quarter dummies. Gender and migration status variables are also included in pooled OLS and IV regressions. Standard errors in parentheses are obtained from bootstrapping (200 iterations) for Panel A and B and adjusted for clustering at individual level in Panel C and D. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A3: Robustness checks

FE-IV regression at:	Mean	Q10th	Q20th	Q30th	Q40th	Q50th	Q60th	Q70th	Q80th	Q90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Baseline (Observations: 53,778; Individuals: 16,687; Mean: 0.03; F statistic: 236.21)										
Home damage	-0.16	-0.28***	-0.15***	-0.23***	-0.23***	-0.03*	-0.11***	-0.08***	-0.11***	-0.08***
	[0.36]	[0.03]	[0.01]	[0.03]	[0.00]	[0.02]	[0.02]	[0.01]	[0.03]	[0.02]
Panel B1: Different LoC construction: the sum of squared measures from each category (Observations: 53,778; Individuals: 16,687; Mean: 0.02; F statistic: 236.21)										
Home damage	-0.10	-0.19***	-0.16***	-0.19***	-0.21***	-0.03	-0.08***	-0.09***	-0.12***	-0.06***
	[0.35]	[0.01]	[0.01]	[0.00]	[0.01]	[0.05]	[0.01]	[0.01]	[0.03]	[0.01]
Panel B2: Different LoC construction: the max score across the seven categories (Observations: 53,778; Individuals: 16,687; Mean: 0.00; F statistic: 236.21)										
Home damage	-0.22									
	[0.39]									
Panel C1: Different instrument: any cyclone within 40 km (Observations: 53,778; Individuals: 16,687; Mean: 0.03; F statistic: 411.31)										
Home damage	-0.48*	-0.32***	-0.16***	-0.20***	-0.22***	-0.30***	-0.10***	-0.08***	-0.08***	-0.09***
	[0.26]	[0.05]	[0.00]	[0.00]	[0.00]	[0.08]	[0.01]	[0.03]	[0.01]	[0.03]
Panel C2: Different instrument: any category 5 cyclone within 100 km (Observations: 53,778; Individuals: 16,687; Mean: 0.03; F statistic: 326.61)										
Home damage	-0.37	-0.29***	-0.16***	-0.21***	-0.24***	-0.09***	-0.09***	-0.04***	-0.08***	-0.05***
	[0.33]	[0.01]	[0.00]	[0.01]	[0.02]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]
Panel D1: Excluding some time variant variables (Observations: 53,778; Individuals: 16,687; Mean: 0.03; F statistic: 237.26)										
Home damage	-0.12	-0.55***	-0.28***	-0.65***	-0.53***	-0.38***	-0.32***	-0.09***	-0.06	-0.19***
	[0.36]	[0.07]	[0.09]	[0.11]	[0.02]	[0.05]	[0.06]	[0.02]	[0.05]	[0.02]
Panel D2: Including equivalised household disposable income (Observations: 53,544; Individuals: 16,629; Mean: 0.03; F statistic: 235.49)										
Home damage	-0.19	-0.32***	-0.33***	-0.29***	-0.32**	-0.19***	-0.12***	-0.17***	-0.16**	-0.07***
	[0.36]	[0.02]	[0.12]	[0.03]	[0.14]	[0.02]	[0.02]	[0.04]	[0.07]	[0.01]
Panel D3: Including individual regular market income (Observations: 53,544; Individuals: 16,629; Mean: 0.03; F statistic: 235.39)										
Home damage	-0.18	-0.50***	-0.19***	-0.30***	-0.26***	-0.21***	-0.07***	-0.06***	-0.09***	-0.07***
	[0.36]	[0.06]	[0.01]	[0.03]	[0.01]	[0.02]	[0.00]	[0.01]	[0.01]	[0.01]
Panel D4: Including individual non-wage irregular income (Observations: 53,431; Individuals: 16,610; Mean: 0.03; F statistic: 236.25)										
Home damage	-0.18	-0.53***	-0.19***	-0.25***	-0.34***	-0.16***	-0.14***	-0.11***	-0.13***	-0.08***
	[0.36]	[0.13]	[0.02]	[0.02]	[0.07]	[0.00]	[0.03]	[0.03]	[0.04]	[0.02]

FE-IV regression at:	Mean	Q10th	Q20th	Q30th	Q40th	Q50th	Q60th	Q70th	Q80th	Q90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel D5: Including individual Australian Government non-income support payments (Observations: 53,499; Individuals: 16,624; Mean: 0.03; F statistic: 236.32)										
Home damage	-0.15	-0.28***	-0.19***	-0.28***	-0.19***	-0.17***	-0.14***	-0.11***	-0.10***	-0.06***
	[0.36]	[0.03]	[0.01]	[0.06]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.00]
Panel D6: Including general health summary (Observations: 53,285; Individuals: 16,595; Mean: 0.03; F statistic: 236.50)										
Home damage	-0.23	-0.17***	-0.12***	-0.15***	-0.12***	-0.12***	-0.06***	-0.09***	-0.15**	-0.04***
	[0.35]	[0.01]	[0.01]	[0.00]	[0.02]	[0.04]	[0.01]	[0.03]	[0.07]	[0.00]

Notes: Estimates for each column and panel is from a separate FE-IV regression. Unless stated otherwise, the instrument is exposure to any cyclone within 100 km. "F statistic" denotes the F statistic for the strength of the excluded instrument in the first stage regression from a two-stage least squares (2SLS) regression at the mean. Unless indicated otherwise, other variables include age (and its square), marital status, education, household size, state/territory dummies, year dummies, and survey quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A4: Impact of cyclone exposures on locus of control at the mean and along the distribution

FE regression at:	Mean	Q10th	Q20th	Q30th	Q40th	Q50th	Q60th	Q70th	Q80th	Q90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Exposure to any cyclone within 40 km (Observations: 94,422; Individuals: 27,699; % affected: 0.36)										
Cyclone exposure	-0.04	-0.04	-0.04	-0.08	-0.06	-0.07	-0.00	-0.06	-0.16**	-0.01
	[0.04]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]	[0.07]	[0.07]	[0.07]	[0.04]
Panel B: Exposure to any category 5 cyclone within 40 km (Observations: 94,422; Individuals: 27,699; % affected: 0.10)										
Cyclone exposure	-0.05	-0.05	-0.03	-0.16	-0.13	-0.14	-0.06	0.01	-0.10	0.04
	[0.08]	[0.18]	[0.18]	[0.15]	[0.13]	[0.14]	[0.11]	[0.10]	[0.14]	[0.07]
Panel C: Exposure to any cyclone within 100 km (Observations: 94,422; Individuals: 27,699; % affected: 1.11)										
Cyclone exposure	0.00	-0.01	0.04	-0.01	-0.01	-0.05	0.00	0.02	-0.04	0.00
	[0.03]	[0.06]	[0.06]	[0.05]	[0.05]	[0.05]	[0.04]	[0.04]	[0.05]	[0.03]
Panel D: Exposure to any category 5 cyclone within 100 km (Observations: 94,422; Individuals: 27,699; % affected: 0.34)										
Cyclone exposure	-0.04	-0.17	-0.03	-0.04	-0.02	-0.07	-0.02	0.04	-0.09	-0.02
	[0.05]	[0.11]	[0.10]	[0.09]	[0.08]	[0.08]	[0.06]	[0.06]	[0.08]	[0.04]

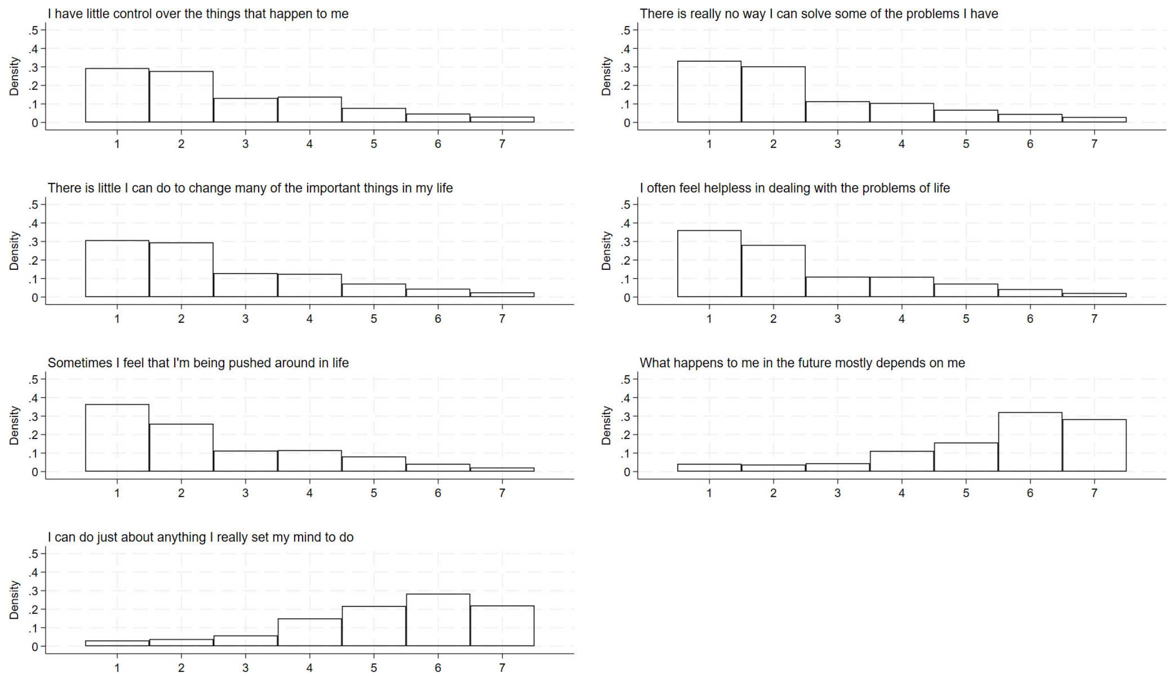
Notes: Estimates for each column and panel is from a separate individual FE regression. Sample: 79,796 observations from 25,683 unique persons. Other variables include age (and its square), marital status, education, household size, state/territory dummies, year dummies, and survey quarter dummies. Robust standard errors clustered at the individual level in parentheses. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Table A5: Heterogenous impact of weather-related home damage on locus of control at the mean and along the distribution

FE-IV regression at:	Mean	Q10th	Q20th	Q30th	Q40th	Q50th	Q60th	Q70th	Q80th	Q90th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A1: Females (Observations: 28,827; Individuals: 8,855; Mean: -0.01, F test statistic: 114.13)										
Home damage	-0.06	-0.46***	-0.14***	-0.17***	-0.18***	-0.17***	-0.10***	-0.04	-0.08**	-0.03
	[0.53]	[0.11]	[0.01]	[0.03]	[0.01]	[0.04]	[0.00]	[0.05]	[0.03]	[0.02]
Panel A2: Males (Observations: 24,951; Individuals: 7,832; Mean: 0.04, F test statistic: 123.07)										
Home damage	-0.25	-0.29***	-0.17***	-0.18***	-0.19***	-0.14***	-0.07***	-0.10***	-0.12***	-0.06***
	[0.48]	[0.03]	[0.06]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]	[0.02]
Panel B1: Young (Observations: 26,621; Individuals: 9,266; Mean: 0.07, F test statistic: 73.13)										
Home damage	-0.13	-0.20***	-0.18***	-0.06	-0.04***	-0.16**	-0.06***	0.09***	-0.11***	-0.14***
	[0.61]	[0.02]	[0.03]	[0.05]	[0.01]	[0.08]	[0.01]	[0.01]	[0.03]	[0.04]
Panel B2: Old (Observations: 24,874; Individuals: 7,797; Mean: -0.01, F test statistic: 137.37)										
Home damage	-0.12	-0.36***	-0.13***	-0.23***	-0.24***	-0.39***	-0.16***	-0.01	-0.22**	0.09***
	[0.50]	[0.05]	[0.01]	[0.02]	[0.01]	[0.08]	[0.02]	[0.03]	[0.09]	[0.02]
Panel C1: Renters (Observations: 16,614; Individuals: 5,375; Mean: -0.10, F test statistic: 70.42)										
Home damage	-0.18	-0.20***	-0.33***	-0.02	-0.20***	-0.20***	-0.23***	-0.24**	-0.01	-0.12***
	[0.62]	[0.02]	[0.12]	[0.03]	[0.01]	[0.04]	[0.02]	[0.10]	[0.02]	[0.01]
Panel C2: Homeowners (Observations: 37,164; Individuals: 11,312; Mean: 0.08, F test statistic: 167.98)										
Home damage	-0.19	-0.27***	-0.13***	-0.23***	-0.09**	-0.03**	-0.07**	-0.07***	0.07	0.06**
	[0.44]	[0.02]	[0.01]	[0.02]	[0.04]	[0.01]	[0.03]	[0.01]	[0.05]	[0.02]
Panel D1: Poorer household (Observations: 27,050; Individuals: 8,511; Mean: -0.12, F test statistic: 121.84)										
Home damage	-0.25	-0.31***	-0.18***	-0.18***	-0.34***	-0.24***	-0.14***	-0.02**	-0.04	0.02**
	[0.52]	[0.02]	[0.06]	[0.02]	[0.03]	[0.03]	[0.01]	[0.01]	[0.03]	[0.01]
Panel D2: Richer household (Observations: 26,728; Individuals: 8,176; Mean: 0.18, F test statistic: 113.77)										
Home damage	-0.08	-0.18***	-0.03	-0.18***	-0.15***	-0.09***	-0.06	-0.08***	-0.13***	-0.08***
	[0.47]	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]	[0.04]	[0.01]	[0.04]	[0.01]

Notes: Estimates for each column and panel is from a separate FE-IV regression. Instrument: Exposure to any cyclone within 100 km. Other explanatory variables include age (and its square), marital status, education, household size, urban, local area socio-economic variables, state/territory dummies, wave dummies, and survey quarter dummies. "Observations", "Individuals", "Mean", and "F test statistic" refer to "Number of observations", "Number of unique individuals", "Mean of locus of control for individuals in the subgroup", and "F statistic for the strength of the excluded instrument in the first stage regression at the mean", respectively. Robust standard errors clustered at the individual level in parentheses. The symbol * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Appendix Figure A1: Histogram of responses for each locus of control statement



Notes: This figure presents the distribution of responses for each locus of control statement, as indicated in the title of each subfigure. Respondents rate their level of agreement or disagreement with each statement on a scale from 1 ("Strongly disagree") to 7 ("Strongly agree"). Sample size: 53,778 observations in the final sample.