Inconsistencies in self-reported weather-related home damage among household members

Nguyen, Ha and Mitrou, Francis

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

Using longitudinal, nationally representative data from Australia, this study uncovers a previously undocumented pattern: in over half of cases where one household member reports weather-related home damage, their co-resident does not. This high rate of intra-household inconsistency is striking, particularly given that respondents are asked the same question within a similar timeframe, and that prior research has generally treated self-reported damage as exogenous to individual behaviour. Household fixed-effects models indicate that a range of factors, including individual health, life satisfaction, local socio-economic conditions, and cyclone exposure, are systematically associated with both the likelihood of reporting damage and intra-household inconsistencies. Individuals in better health, with higher life satisfaction, or residing in more advantaged areas are less likely to report damage—whether consistently or inconsistently—relative to their household member. Furthermore, replacing self-reported damage with a more objective measure substantially attenuates the observed associations between damage and individual health and life satisfaction. Taken together, these findings challenge the common assumption of exogeneity in self-reported weather-related home damage and underscore the risk of biased inference if endogeneity is not adequately addressed.

Keywords: Measurement Errors; Survey Misreporting; Natural Disasters; Cyclones; Housing

JEL classifications: C18; R23; Q54

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[*] **Corresponding author**: The Kids Research Institute Australia | Postal: GPO Box 855, Perth WA 6872, Australia | Email: ha.nguyen@thekids.org.au.

[†] The Kids Research Institute Australia & The University of Western Australia, Australia.

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1. Introduction

Self-reported weather-related home damage has been widely used as a key explanatory variable in empirical models examining the impact of natural disasters on various life outcomes (Baryshnikova & Pham 2019; Johar *et al.* 2022; Mitchell *et al.* 2024; Li & Leppold 2025; Nguyen & Mitrou 2025a). However, the accuracy of this commonly used measure remains largely unexamined. This gap in the literature is particularly important to address given the growing concerns about the effects of natural disasters and the increasing availability and use of such self-reported data (Dell *et al.* 2014; Carleton *et al.* 2022). Moreover, most existing studies treat self-reported weather-related home damage as exogenous to individual behaviour when assessing its effects on multiple life outcomes (Johar *et al.* 2022; Gunby & Coupé 2023; Li *et al.* 2023; Bernard *et al.* 2024; Mitchell *et al.* 2024). Whether this assumption holds in practice—and the consequences for estimated relationships if it does not—remains unclear.

This study addresses these gaps by being the first to examine discrepancies in self-reports of weather-related home damage across household members. It also investigates the determinants of within-household inconsistencies in reported damage, as well as the implications of using self-reported damage measures when analysing their effects on mental health, subjective well-being, and financial outcomes.

We use nationally representative longitudinal data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which asks all responding household members the same set of questions—within a similar timeframe—about whether their home was damaged by a weather-related disaster. This design allows for reliable within-household comparisons (e.g., between spouses or parents and children), while minimizing the impact of timing differences. The panel structure and rich individual- and household-level information further enable a detailed investigation of the determinants of within-household inconsistencies in reported damage and the broader implications for analyses using such data. The use of this widely cited dataset—already extensively applied in studies of weather-related damage and life outcomes—also helps situate our contribution within a growing and policy-relevant body of literature (Summerfield *et al.* 2024).

This study contributes to a substantial literature on the socio-economic consequences of natural disasters (Dell *et al.* 2014; Botzen *et al.* 2019; Carleton *et al.* 2022). Within this broader field, our research aligns more closely with a growing body of work examining the effects of extreme weather events on home damage and, subsequently, the impact of such damage on various life outcomes (Baryshnikova & Pham 2019; Nguyen & Mitrou 2024b, 2025a). More specifically, it complements a number of studies that use the same data source to explore the relationship between weather-related home damage and outcomes such as mental health (Baryshnikova & Pham 2019; Mitchell *et al.* 2024; Li & Leppold 2025), financial outcomes (Johar *et al.* 2022), health and housing outcomes (Li *et al.* 2023), life satisfaction (Gunby & Coupé 2023; Nguyen & Mitrou 2024a), migration (Bernard *et al.* 2024), and locus of control (Nguyen & Mitrou 2025a).

Most of these studies treat weather-related home damage as an exogenous shock and employ individual fixed-effects models to enhance causal inference (Johar *et al.* 2022; Gunby & Coupé 2023; Li *et al.* 2023; Bernard *et al.* 2024; Mitchell *et al.* 2024). Others adopt instrumental variable approaches to address concerns over endogeneity (Baryshnikova & Pham 2019; Nguyen & Mitrou 2024a, 2025a), often reporting substantial differences in estimated effects compared to fixed-effects models. These findings suggest that self-reported damage may not be strictly exogenous, as it may correlate with both observable and unobservable time-varying characteristics linked to the outcomes of interest. However, while these studies highlight concerns about the endogeneity of self-reported damage, none has examined potential inconsistencies in reporting within households, nor the determinants and implications of such discrepancies, as this study does.

By evaluating the reliability of self-reported weather-related home damage, this study also contributes to the broader literature on measurement error in survey data (see Bound *et al.* (2001); Meyer *et al.* (2015); DiTraglia and García-Jimeno (2019); Schennach (2020) for excellent reviews). More specifically, it aligns with research on the prevalence and implications of misreported exposure to natural disasters, as well as methodological efforts to address such errors (Dell *et al.* 2014; Hsiang & Kopp 2018; Botzen *et al.* 2019). While the challenges associated with measurement error in disaster exposure are increasingly recognised (Hsiang & Jina 2014; Guiteras *et al.* 2015; Nguyen & Nguyen 2020; Gallagher 2023), to our knowledge, no prior studies have investigated intra-household inconsistencies in the reporting of weather-related home damage or analysed their determinants and implications—issues that are central to this study. The findings presented here are relevant not only to studies using Australian data, such as our own, but also to a broader body of research that relies on self-reported measures of natural disaster exposure. Given the growing concerns about the impacts of climate change, the number of such studies is rapidly increasing (Dell *et al.* 2014; Hsiang & Kopp 2018; Botzen *et al.* 2019; Nguyen & Mitrou 2024a).

Using longitudinal, nationally representative data from Australia, this study presents three key findings. First, it reveals a previously undocumented pattern in self-reported weather-related home damage: in more than half of the cases where one household member reports damage, their co-residing relative does not. This high rate of intra-household inconsistency is striking, particularly given that respondents are close family members (e.g., spouses or parent–child pairs), surveyed within a similar timeframe.

Second, using household fixed-effects models, we find that various factors—including individual health, life satisfaction, local socio-economic conditions, and exposure to tropical cyclones—are associated not only with the likelihood of reporting home damage but also with the probability of inconsistent reporting within households. While specific associations vary, the overall pattern suggests that individuals with better health or life satisfaction, or those living in more socio-economically advantaged areas, are less likely to report damage—either consistently or inconsistently—relative to their household member. In contrast, financial factors appear unrelated to the likelihood of reporting weather-related home damage, whether consistently or inconsistently. Furthermore, focusing on couple pairs, we find that better health—particularly mental health—and higher life satisfaction are associated with reduced inconsistency in self-reported weather-related home damage, with the effects of husbands' health appearing marginally stronger than those of wives.

Third, our results indicate that employing more objective measures of home damage would substantially attenuate the observed associations between weather-related damage and individual health and life satisfaction. Together, these findings question the assumption of exogeneity commonly applied to self-reported weather-related home damage and highlight the need to address potential endogeneity when estimating its causal effects.

The remainder of the paper is structured as follows. Section 2 describes the data and presents descriptive analyses. Section 3 outlines the empirical models used to examine the determinants of consistent and inconsistent reporting of weather-related home damage within households and presents the main findings. Section 4 investigates additional factors—including exposure to local tropical cyclones—that influence both the likelihood of reporting home damage and the (in)consistency of such reporting across household members. Section 5 examines the implications of using inconsistently reported home damage when assessing its effects on health, life satisfaction, and financial outcomes. Section 6 concludes.

2. Data, sample, and descriptive analysis

2.1. Data

To examine the (in)consistency in self-reported home damage among household members, we utilize data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey

(Summerfield *et al.* 2024). This nationally representative longitudinal survey, initiated in 2001 and conducted annually, is particularly well-suited for this analysis for three key reasons. First, it surveys all individuals aged 15 and over in private households over time, enabling comparisons of responses among co-residing household members. Second, all responding household members are administered the same set of questions within a similar timeframe, allowing for reliable comparisons of their responses and minimizing the influence of temporal variation. Third, the survey provides rich individual- and household-level data, supporting a detailed investigation of the potential determinants of within-household differences (if any) in self-reported home damage, as well as the broader implications of using such self-reported measures. This study draws on Release 23 of the HILDA Survey, which spans the period from 2001 to 2023.

2.2. Outcome variables

Our main outcome of interest is weather-related home damage, which is derived from responses to the survey question: "Did any of these events occur to you in the past 12 months?", specifically the item: "A weather-related disaster (e.g., flood, bushfire, cyclone) damaged or destroyed your home". This measure is available from Wave 9 of the HILDA Survey onwards (Summerfield *et al.* 2024). We focus on this self-reported measure for three main reasons. First, as noted above, the question is administered to all household members aged 15 and over within a similar timeframe (discussed further below), enabling reliable comparisons across respondents and minimizing temporal biases. Second, the data allow us to identify relationships among household members and focus on closely related individuals—such as spouses, and parents and children—who co-reside in the same dwelling and are therefore expected to be equally exposed to any natural disaster affecting the home. All else being equal, we would expect these individuals to have a similar likelihood of reporting such damage.[1]

Third, as documented above, the same self-reported measure of weather-related home damage has been used extensively in Australian studies examining its effects on various socio-economic and health outcomes, with most treating it as an exogenous shock (Johar *et al.* 2022; Gunby & Coupé 2023; Li *et al.* 2023; Bernard *et al.* 2024; Mitchell *et al.* 2024). This study is the first to investigate discrepancies in self-reports of weather-related home damage across household members, as well as the potential contributing factors—such as mental health, life satisfaction, and financial circumstances—that have featured prominently in prior work. These findings aim to inform the interpretation and use of this self-reported measure in future research. This contribution is particularly salient given the growing number of studies that rely on this measure as a proxy for natural disaster exposure when assessing a broad range of socio-economic outcomes.

As in previous Australian studies using the HILDA Survey, we measure weather-related home damage as a binary variable that takes the value of one if the respondent reported that the home they lived in was damaged by a weather-related disaster in the 12 months prior to the survey, and zero otherwise. This variable is constructed at the individual level for all household members, as each responding member (i.e., individuals aged 15 and over, regardless of homeownership or marital status) is expected to provide a separate and independent response to this question (Summerfield *et al.* 2024). Additionally, we construct a household-level binary

[1] While the HILDA Survey includes a wide range of self-reported life events related to health, finances, employment, and family circumstances (see Nguyen *et al.* (2024b), for details), we do not focus on these outcomes, as they are typically highly individual-specific and may not affect all household members in the same way. Moreover, most of these events are unlikely to be directly caused by natural disasters and are therefore more susceptible to endogeneity concerns. In contrast, natural disasters are generally considered exogenous events, making disaster-related home damage a more suitable outcome for our analysis.

indicator that takes the value of one if a majority (i.e., ≥50%) of the other responding household members—excluding the individual in question—report home damage, and zero otherwise.

Building on the binary variables described above, we use information on relationships among co-residing household members to construct three variables that capture reporting (in)consistency across four types of household member pairs: (i) spouses (i.e., husband and wife), (ii) mother and child, (iii) father and child, and (iv) an individual versus all other household members (typically including the spouse, parents, and children). For each pair type, we compare responses and classify them into four mutually exclusive categories: (1) neither member reported home damage (the reference group); (2) both reported home damage; (3) the individual reported damage while the other did not; and (4) the individual did not report damage while the other did. The first two categories represent concordant non-reporting and reporting, respectively, while the latter two capture discordant reporting.

In our analysis, we treat the concordant reporting (both reported damage) and the two discordant categories as separate binary outcomes, with concordant non-reporting (i.e., neither member reported damage) serving as the comparison group and coded as zero in all three cases. We also construct a combined binary indicator that equals one if any discrepancy exists between the pair's reports and zero if their responses are aligned. This approach yields four binary outcome variables, each indicating whether a match (as in the case of both reporting damage) or a mismatch in self-reported home damage exists within a given pair type.

2.3. Sample

Because this study aims to compare responses among household members, we restrict the sample to individuals with at least one responding co-residing household member. In addition, we necessarily limit our main analysis to individuals surveyed from Wave 9 of the HILDA Survey onward, as the main outcome variable—weather-related home damage—is not available in earlier waves (Summerfield *et al.* 2024). We further restrict the sample to pairs with non-missing information on key covariates used in the empirical regression models (discussed in detail below in Section 3.1).

After applying these restrictions, the final analytical sample size—depending on the type of household pair—ranges from approximately 16,000 individuals for child–father pairs to around 177,000 individuals for individual–all-other-household-member comparisons. Correspondingly, the number of unique households ranges from about 5,400 for child–father pairs to approximately 21,000 for individual–all-other-household-member comparisons. These individuals and households were surveyed between 2009 and 2023.

2.4. Descriptive analysis

Table 1 presents the rates of self-reported weather-related home damage by relationship to other household members. The event is relatively rare, with only approximately 1.6% of individuals in our sample reporting such damage in the 12 months preceding the survey (see last row, Column 4). However, comparisons between household member pairs reveal substantial discrepancies in reporting. For instance, Panel A shows that 1,226 individuals reported home damage while their spouses did not, compared to only 904 couples in which both partners reported damage. This implies that among the 2,130 couples where at least one partner reported home damage, 58% exhibited disagreement in their responses.

The discrepancy is even greater among parent–child pairs. In both child–mother and child–father comparisons (Panels B and C, respectively), approximately 70% of pairs in which at least one member reported damage showed inconsistent reporting. Similarly, among individual–all-other-household-member pairs (Panel D), 61% reported inconsistently when at least one person reported damage.

Overall, these descriptive results indicate that while some household members agree in their reports of weather-related home damage, a substantial proportion do not. In fact, in more than half of the cases where any member of a pair reports damage, the co-residing relative does not report the same. This discrepancy in self-reporting is particularly striking given that these individuals live in the same dwelling and were surveyed at approximately the same time. As shown in Appendix Figure A1, which presents the distribution of differences in survey dates within the same wave, there is minimal variation in survey timing across household member pairs—ranging from zero days for couples to an average of 3.43 days for child–mother pairs. To the best of our knowledge, these notable discrepancies in self-reports within households have not been previously documented.

In the following sections, we examine potential factors contributing to these reporting discrepancies. In this regard, Table 2 compares key characteristics of individuals in the "inconsistent reporting" group—those whose reports of weather-related home damage in the past year differ from those of other household members—and the "consistent reporting" group, comprising individuals whose reports align with those of their co-residing household members. Descriptions and summary statistics of the main variables are provided in Appendix Table A1. Compared to the "consistent reporting" group, individuals in the "inconsistent reporting" group tend to be younger, less likely to have been born in a non-English-speaking background (NESB) country, and less educated, as reflected in a lower likelihood of having completed a bachelor's degree or higher. They are also more likely to live in larger households or rented homes.

Moreover, individuals in the "inconsistent reporting" group face greater socio-economic challenges: they are more likely to reside in areas with lower Socio-Economic Indexes for Areas (SEIFA) scores or in non-major city regions, although these areas have lower unemployment rates. Their homes are also more likely to be reported as damaged by weather-related events—either by themselves or by other household members. Furthermore, they exhibit worse outcomes across multiple domains, including mental health, physical functioning, general health, life satisfaction, and financial well-being.

3. Determinants of (in)consistency in self-reported home damage

3.1. Empirical model

We estimate the following model to examine the factors associated with (in)consistencies in self-reported weather-related home damage for individual i, residing in household j in year t:

$$Y_{ijt} = \alpha + X_{ijt}\boldsymbol{\beta} + \gamma_t + \delta_M + \varepsilon_j + \mu_{ijt} \tag{1}$$

In equation (1), Y_{ijt} denotes one of the four previously defined binary variables indicating whether there is (in)consistency in the reporting of home damage between members of a given responding household pair. X_{ijt} represents a vector of covariates at the individual, household, and local area levels. Drawing on the literature on misreporting (Bound *et al.* 2001; Meyer *et al.* 2015; Nguyen *et al.* 2023), and to address concerns regarding the potential endogeneity of included variables, we employ a parsimonious set of explanatory variables in the baseline regression model.

At the individual level, controls include age (and age squared), gender, migration status, and educational attainment. At the household level, we control for the number of household members, homeownership status (i.e., homeowner versus renter), and an indicator for residence in a major city. To account for spatial and temporal variation in reporting behaviour, we include state/territory fixed effects, survey year fixed effects (γ_t) and survey month fixed effects (δ_M). We also incorporate local contextual factors that may influence self-reporting, such as the regional unemployment rate and SEIFA scores, recognizing that some regions are more prone to natural disasters (Dell *et al.* 2014; Hsiang & Kopp 2018; Botzen *et al.* 2019), which may influence individuals' likelihood of reporting home damage (Nguyen & Mitrou 2024b).

Several of the included variables are motivated by commonly cited sources of misreporting (Bound *et al.* 2001; Celhay *et al.* 2024).[2] For instance, education is included to capture potential effects of cognitive ability on reporting accuracy. Homeownership status is included to examine whether renters—who typically have less attachment to and responsibility for property maintenance—are less likely than homeowners to consistently report damage (Call *et al.* 2022; Meyer *et al.* 2022). Additionally, the inclusion of survey month dummies (δ_M) helps control for variation in recall periods due to differences in interview timing within household member pairs.

We leverage the panel structure of the HILDA data to control for unobserved, time-invariant household-level characteristics (ε_j), such as marital sorting preferences or residential preferences, which may influence both the likelihood of reporting damage and the covariates included in X_{ijt} (Wooldridge 2010; Dell *et al.* 2014; Hsiang & Kopp 2018). The inclusion of household fixed effects is particularly important for our research design, which relies on comparing self-reported responses among household members. In Equation (1), μ_{ijt} represents the idiosyncratic error term, while α and $\boldsymbol{\beta}$ are vectors of parameters to be estimated, with $\boldsymbol{\beta}$ being the primary vector of interest. Estimates of $\boldsymbol{\beta}$ from this household fixed effects model, which accounts for unobserved, time-invariant heterogeneity at the household level, are thus identified by within-household variation in both the outcome and the explanatory variables—enhancing the credibility of the causal interpretation.

The model is estimated using Ordinary Least Squares (OLS) method. Consistent with standard practice for binary outcome variables in panel data settings, we employ a household fixed

[2] For a comprehensive overview, see Bound *et al.* (2001), who classify the determinants of misreporting into three broad categories: cognitive processes, social desirability, and survey-related conditions. It is important to note that while we draw on the misreporting literature due to its relevance, we do not make assumptions regarding which respondent in a given household pair provides a more accurate report of home damage. Doing so would require external validation using alternative data sources with more objective measures—such as administrative records or insurance claims—which are beyond the scope of this study and remain a task for future research.

effects linear probability model (LPM). While the LPM has certain limitations, it remains widely used due to its computational simplicity and ease of interpretation (Angrist & Pischke 2009; Wooldridge 2010). To account for potential serial correlation, we cluster standard errors at the household level (Cameron & Miller 2015). For brevity and analytical focus, we apply this regression model—and all subsequent models—to two household pair types: spouses and individuals with all other household members. These groups have the largest sample sizes and therefore allow for more robust statistical analysis.[3]

3.2. Main empirical results

The results from household fixed effects regressions, conducted separately for two types of household member pairs, are presented in Table 3. While most individual- and household-level covariates are not statistically significant, several factors are significantly associated (at the 5% level or better) with the probability of consistent or inconsistent reporting of weather-related home damage, depending on the household pair.

For example, among co-residing couples, males (i.e., husbands) are more likely to report home damage in cases where their wives do not (Column 2). Additionally, individuals born in non–English-speaking background (NESB) countries, as well as their spouses, are less likely to report home damage (Column 1). Higher-educated individuals—those with a bachelor's degree or higher—are less likely to report inconsistently (Column 8), primarily because they are less likely to report no home damage when their household member reports some damage (Columns 3 and 7). This finding is consistent with prior evidence from the misreporting literature, which suggests that greater cognitive ability—sometimes proxied by education—may help reduce reporting errors (Bound *et al.* 2001; Nguyen *et al.* 2023; Celhay *et al.* 2024).

[3] Unreported results based on mother–child and father–child pairs generally lack statistical significance, likely due to relatively small sample sizes—particularly the limited number of individuals in each pair who reported any home damage.

Table 3 also shows that, compared to renters, homeowners are more likely to report home damage and to do so consistently with other household members (Columns 1 and 5). They are also less likely to report inconsistently across various forms of disagreement (Columns 2, 4, 6, and 8). This pattern holds across both spouse pairs and individual–all other household member pairs. These findings support our earlier hypothesis that homeowners—owing to their greater attachment to and responsibility for property maintenance—are more likely to report home damage consistently and less likely to report inconsistently.

We also find that two indicators of local socio-economic conditions—the SEIFA scores and major city status—are negatively associated with both consistent and inconsistent reporting of home damage. Specifically, individuals living in areas with higher SEIFA scores are less likely to report any home damage in agreement with household members (Columns 1 and 5) and are also less likely to report inconsistently (remaining columns). Similarly, those residing in major cities are less likely to report inconsistently (Columns 2 to 4 and 6 to 8). These patterns are observed consistently for both types of household member pairs.

Overall, these results suggest that only a subset of individual and household characteristics—notably education and homeownership—are statistically associated with reporting (in)consistency. In addition, individuals in more socio-economically advantaged areas (i.e., with higher SEIFA scores or in major cities) are less likely to report damage, either consistently or inconsistently, with other household members. The broadly similar patterns across both household pair types likely reflect that most individual–all other household member pairs include spouses. For brevity and analytical focus, the following sections will focus on individual–all other household member pairs, unless otherwise noted.

4. Other results

4.1. Additional determinants of (in)consistency in self-reported home damage

This subsection further investigates additional factors associated with (in)consistencies in the self-reporting of weather-related home damage. Motivated by prior evidence on correlates of misreporting (Bound *et al.* 2001; Celhay *et al.* 2024) and the well-documented relationship between weather-related home damage and various health and wellbeing outcomes (Baryshnikova & Pham 2019; Johar *et al.* 2022; Gunby & Coupé 2023; Mitchell *et al.* 2024; Li & Leppold 2025), we examine the association between several such factors and the likelihood of (in)consistent self-reporting. Specifically, we extend Equation (1) by including, separately, one of the following six explanatory variables: (1) mental health, constructed using the Short Form (SF-36) Health Survey (Summerfield *et al.* 2024); (2) SF-36 physical functioning; (3) SF-36 general health; (4) overall life satisfaction; (5) individual regular market income; and (6) equivalised household disposable income. Brief descriptions of these variables are provided in Appendix Table A1.

For ease of interpretation, the first four variables—related to health and life satisfaction—are standardized, and for all six variables, higher values indicate more favourable outcomes. To address potential endogeneity concerns (e.g., the possibility that weather-related home damage affects these outcomes), each variable is included in its one-year lagged form in the modified specification of Equation (1), where the outcome—home damage—is measured in the current year. Moreover, to maintain focus and brevity, this subsection concentrates on individual–all-other-household-member pairs.[4]

Table 4 presents the estimates for the additional variables, revealing statistically significant associations between selected factors and the probability of (in)consistency in self-reporting of weather-related home damage among household members. Specifically, the negative and

[4] Appendix Table A2 presents similar findings for spouse pairs.

highly significant (at the 1% level) coefficients on the one-year lagged mental health variable across all regressions (Panel A) suggest that individuals with better mental health are less likely to report home damage concordantly with the majority of their household members (i.e., both the individual and most co-residing members reported damage; Column 1) in the following year. They are also less likely to exhibit discrepancies in their self-reported home damage relative to other household members (Columns 2 to 4).

Similarly, the negative and highly significant coefficients on the one-year lagged physical functioning (Panel B) and general health (Panel C) variables in three out of four regressions indicate that individuals with better physical or general health are less likely to report home damage concordantly with the majority of their household members and are also less likely to exhibit reporting discrepancies—particularly instances where they report damage while the other household member does not (Column 2). Likewise, the negative and highly significant coefficients on the one-year lagged life satisfaction variable (Panel D) in three out of four regressions suggest that individuals with greater life satisfaction are less likely to exhibit inconsistencies in self-reported home damage (Columns 2 to 4).

In contrast, the statistically insignificant coefficients for the two variables capturing financial outcomes—individual market income (Panel E) and equivalised household disposable income (Panel F)—suggest that these financial factors are not meaningfully associated with (in)consistency in self-reporting of home damage in our sample.

Overall, these results suggest that health and life satisfaction factors are more strongly and consistently associated with (in)consistency in self-reported home damage than financial factors. Among the three health-related variables considered, mental health appears to have the most pronounced effect, as indicated by the larger absolute coefficient values and higher levels of statistical significance compared to those for physical or general health. Moreover, the finding that individuals with better health—particularly mental health—and greater life satisfaction are less likely to exhibit inconsistencies in self-reported home damage aligns with prior evidence from the misreporting literature. This literature suggests that higher cognitive ability—often proxied by mental health—may reduce recall errors and, consequently, the likelihood of misreporting (Bound *et al.* 2001; Nguyen *et al.* 2023; Celhay *et al.* 2024).

4.2. Effects of own and spouse's health and life satisfaction

The preceding results suggest that an individual's own health and life satisfaction play a significant role in explaining (in)consistencies in self-reported weather-related home damage within households. Given that this analysis compares self-reports across household members, it is plausible that both the individual's and their co-residing partner's health and life satisfaction influence reporting (in)consistencies.

To investigate this possibility, we extend the previous empirical approach by incorporating—one at a time—each of the four health and life satisfaction variables previously identified as significantly associated with reporting (in)consistencies. These variables are included in Equation (1) in their one-year lagged form, using values reported for both the individual and their co-residing partner. For brevity, clarity, and analytical robustness, the analysis focuses on couple pairs. Furthermore, to explore potential gender differences, the model is estimated separately for females (wives) and males (husbands).

Table 5 presents the regression results, revealing three notable patterns.[5] First, the coefficients for all three health variables—measured for both husbands and wives—are negative and statistically significant at the 1% level in the regressions where both partners report home damage (Panels A, B, and C; Columns 1 and 2). This indicates that couples in better health are less likely to report home damage in the following year. Notably, the magnitudes of these

[5] We also experimented with including spousal education variables, which have been shown to significantly affect (in)consistent reporting, but found little evidence that a spouse's education has a statistically significant effect on an individual's (in)consistent reporting behaviour.

effects are similar for husbands and wives. In contrast, the statistically insignificant coefficients on the one-year lag of both own and spouse's life satisfaction (Panel D; Columns 1 and 2) suggest that life satisfaction is not significantly associated with the likelihood that both partners report home damage in the subsequent year.

Second, the additional estimates for the three health variables—reported in Panels A, B, and C; Columns 3 to 8—indicate that health factors are also associated with inconsistencies in self-reported home damage in the following year. Specifically, couples in better health are less likely to exhibit inconsistent reporting. The strength of these associations varies by health indicator, by whether the variable pertains to the husband or wife, and by the type of reporting inconsistency. Among the three measures, mental health shows the most pronounced effects, as evidenced by larger absolute coefficient values and greater statistical significance. Moreover, husbands' health appears to play a more prominent role than wives', with consistently larger and more significant coefficients.

Third, the estimates for life satisfaction reported in Panel D (Columns 3 to 8) suggest that couples with higher life satisfaction are also less likely to exhibit inconsistent reporting. Furthermore, there is no clear gender difference in this association, as the coefficients for husbands and wives are of similar magnitude and significance.

Overall, the results presented in this subsection suggest that couples in better health are less likely to report home damage in the subsequent year. Furthermore, better health—particularly mental health—and higher life satisfaction are associated with reduced inconsistency in self-reported weather-related home damage among couples, with the effects of husbands' health appearing marginally stronger than those of wives.

4.3. Determinants of weather-related home damage and (in)consistency in self-reporting

To further investigate the determinants of (in)consistency in self-reporting, this section examines the factors associated with reports of weather-related home damage. Specifically, we estimate an empirical household fixed-effects model similar to Equation (1), but with a binary outcome variable indicating whether an individual reported any weather-related home damage in the 12 months preceding the survey.

Moreover, drawing on the recent Australian study by Nguyen and Mitrou (2024b), which explicitly examines the impact of cyclones on residential relocation and home damage, we include a plausibly exogenous variable capturing whether the respondent resided in a postcode affected by a tropical cyclone (within 100 km of the cyclone's eye) in the 12 months prior to the survey date.[6] The coefficient estimate for this cyclone exposure variable can be interpreted as causal, as this measure is objectively derived and plausibly exogenous to individual behaviour. Furthermore, the inclusion of household fixed effects helps control for unobserved time-invariant factors, such as preferences for residential location, that may be correlated with exposure to natural disasters (Wooldridge 2010; Dell *et al.* 2014; Botzen *et al.* 2019).[7]

Motivated by earlier findings indicating a strong statistical association between local area characteristics—such as the SEIFA scores and major city classification—and the probability of (in)consistent reporting, we also include the cyclone exposure variable in the baseline model examining determinants of (in)consistency in self-reporting. Given that tropical cyclones are

[6] Following the methodology outlined by Nguyen and Mitrou (2024b, 2025b), we measure individual exposure to cyclones by incorporating both the proximity to the cyclone's eye and its intensity. This is achieved by linking the HILDA survey data to the publicly available historical cyclone database from the Australian Bureau of Meteorology. We align the cyclone paths and dates with respondents' postcode centroids and interview dates from HILDA. Our analysis uses the restricted-access version of HILDA, which provides the highest available level of geographic detail (Summerfield *et al.* 2024).

[7] The estimates of cyclone exposure remain largely unchanged when controlling for individual fixed effects—as done by Nguyen and Mitrou (2024b, 2025b)—rather than household fixed effects, as employed in the present analysis. We employ this measure of cyclone exposure to ensure a sufficiently large number of affected individuals, thereby enabling a robust analysis. As shown in the last row of Table 6, approximately 3% of individuals in our sample were exposed to at least one cyclone within 100 km of its eye. This substantial proportion of affected individuals enhances our ability to detect the effect of cyclone exposure on home damage.

explicitly mentioned in the survey prompt as a type of natural disaster that may cause home damage, we hypothesize that exposure to such events may influence both the likelihood of an individual reporting home damage and the probability of reporting discrepancies among household members. For brevity and focus, this subsection examines a single binary outcome—whether any discrepancy exists between individuals in any of the two previously defined pairs—as this provides the largest sample size and thus supports more robust analysis. We continue to apply both regression models to two types of household member pairs: spouse pairs and individual–all other household member pairs, for similar reasons.

The results of these analyses are presented in Table 6. The odd-numbered columns report the estimated determinants of self-reported weather-related home damage. The findings indicate that most individual- and household-level socio-demographic variables included in the model are not statistically significant predictors. This pattern is consistent with the notion that, once survey timing and household fixed effects are controlled for, home damage resulting from extreme weather events is largely uncorrelated with basic individual and household characteristics.[8] By contrast, certain area-level characteristics are significantly associated with the likelihood of reporting weather-related home damage.

Specifically, individuals residing in more socio-economically advantaged areas—indicated by higher SEIFA scores or residence in major cities—are less likely to report weather-related home damage. This may reflect either a greater capacity to mitigate the impacts of natural disasters in these areas or the lower inherent exposure to such events, as documented in prior literature (Dell *et al.* 2014; Hsiang & Kopp 2018; Nguyen & Mitrou 2024b).

[8] As discussed in Subsection 4.1, a parsimonious set of covariates is included in these regressions to address concerns about endogeneity. However, unreported regressions—where selected health, life satisfaction, and financial variables (as outlined in Subsection 4.3) are additionally and separately controlled for— suggest that individuals with poorer mental, physical, or general health, as well as lower life satisfaction, are more likely to report home damage.

Notably, the estimated coefficients on cyclone exposure are positive and statistically significant at the 1% level across all specifications. These findings align with earlier Australian evidence reported by Nguyen and Mitrou (2024b, 2025b), which suggests that individuals exposed to a cyclone are more likely to report weather-related damage to their homes. For example, estimates for individual–all other household member pairs indicate that individuals exposed to any cyclone within 100 kilometres of its eye in the past 12 months are approximately 1.64 percentage points more likely to report such damage (Column 3). This effect is substantial in relative terms, representing approximately 98.8% of the sample mean, which is only 1.66%.

A comparison of the determinants of reporting any weather-related home damage and the inconsistency in such reporting among household member pairs—particularly for the sample including all household members, where the larger sample size increases the statistical power of the regression (Columns 3 and 4)—yields several noteworthy insights. For instance, individuals with higher education, measured by the attainment of a bachelor's degree or higher, exhibit a lower probability of reporting home damage (Column 3). This may reflect their greater capacity to prepare for and mitigate the effects of natural disasters (Dell *et al.* 2014; Botzen *et al.* 2019). These more highly educated individuals are also less likely to report home damage inconsistently compared to other household members, as shown in Column 4. This pattern is consistent with baseline findings and is similarly observed for other explanatory variables. Notably, higher educational attainment is associated with both a lower likelihood of reporting weather-related home damage and a reduced likelihood of inconsistent reporting within households. This pattern suggests that education may not only mitigate the direct adverse impacts of natural disasters but also enhance the reliability of self-reported damage information.

Furthermore, while homeownership status is not significantly associated with the probability of reporting home damage (Columns 1 and 3), it is significantly associated with a lower probability of inconsistent reporting (Columns 2 and 4). This finding supports our earlier hypothesis that homeowners, due to their stronger attachment to and responsibility for the property, are more likely to report home damage consistently within the household.

In addition, estimates for the two local area socio-economic variables—SEIFA scores and major city status—consistently indicate that individuals residing in more advantaged areas are both less likely to report home damage and less likely to report it inconsistently.

Similarly, the cyclone exposure variable is positively and statistically significantly associated (at least at the 5% level) with both the likelihood of reporting weather-related home damage and the likelihood of inconsistent reporting among household members. Specifically, individuals residing in postcodes affected by any cyclone within 100 km of its eye are more likely to report home damage and more likely to report it differently from other household members, including their spouses.

Taken together, these results suggest that several observable characteristics—especially local-area factors such as socio-economic conditions and recent exposure to cyclones—are strongly correlated with both the probability of reporting weather-related home damage and the likelihood of reporting discrepancies within households. Notably, these findings are robust to the inclusion of household fixed effects and a relatively comprehensive set of time-varying and time-invariant covariates. This suggests that self-reported weather-related home damage may be influenced by a range of factors—including both time-varying and time-invariant characteristics—and therefore should not necessarily be treated as exogenous, as is often assumed in the existing literature.

5. Effects of using inconsistently self-reported weather-related home damage

This subsection examines the potential implications of using inconsistently self-reported weather-related home damage when assessing its effects on various health, life satisfaction and financial outcomes. To this end, we employ an individual fixed-effects (FE) model—consistent with most prior studies using the same dataset (Johar *et al.* 2022; Gunby & Coupé 2023; Mitchell *et al.* 2024; Li & Leppold 2025) —to estimate the impact of weather-related home damage on six outcomes. These outcomes, described in more detail in Subsection 4.1, include individual mental health, physical functioning, general health, overall life satisfaction, regular market income, and equivalised household disposable income.

Our regressions control for a parsimonious set of covariates similar to those in X_{ijt} in Equation (1), along with state/territory fixed effects, survey year fixed effects, and survey month fixed effects. In this modified individual FE regression specification, we include—separately—two indicators of weather-related home damage: (1) self-reported by the individual, and (2) reported by the corresponding co-residing household member. The use of an individual's own report of home damage follows prior studies. However, we also incorporate the co-residing partner's report to examine whether relying solely on an individual's report may yield biased estimates due to measurement error or reporting inconsistencies. This approach is motivated by a substantial body of research that uses more objective measures to address potential endogeneity concerns associated with self-reported variables (Bound *et al.* 2001; Meyer *et al.* 2015).

The results from this analysis are presented in Table 7 and reveal two main findings. First, consistent with prior studies, our individual FE estimates (shown in the odd-numbered columns) indicate that self-reported home damage is strongly and negatively associated with health outcomes—including mental health, physical functioning, and general health (Mitchell *et al.* 2024; Li & Leppold 2025)—and marginally negatively associated with life satisfaction (Gunby & Coupé 2023; Nguyen & Mitrou 2024a), but not significantly associated with any financial outcomes (Johar *et al.* 2022). These results suggest that individuals who report experiencing weather-related home damage also tend to report poorer health and lower life satisfaction. This pattern mirrors earlier findings presented in Subsection 4.1, which indicate that individuals with poorer health and lower life satisfaction are more likely to report such damage, whereas financial factors do not appear to influence the likelihood of reporting home damage.

Second, when using weather-related home damage reports provided by other household members (as shown in the even-numbered columns), the estimated effects on all health and life satisfaction outcomes become statistically insignificant, while those for the two financial outcomes remain statistically insignificant. The reduction in both the magnitude and statistical significance of the health and life satisfaction coefficients—relative to estimates based on self-reported damage—is consistent with our earlier finding that individuals in poorer health and life satisfaction are more likely to report such damage. This suggests that using a more objective measure of home damage—one less directly correlated with individual health and life satisfaction—would yield a substantially weaker relationship between weather-related home damage and these well-being outcomes. This interpretation aligns with prior findings by Le and Nguyen (2017, 2018), who demonstrate that the association between maternal health and child development is considerably attenuated when child outcomes are reported by third parties (e.g., teachers or spouses) rather than by mothers themselves.

The results presented above suggest that relying on self-reported weather-related home damage—particularly when such reports are inconsistently provided across household members—may lead to biased estimates of its effects on health and life satisfaction. A similar concern, though in relation to other self-reported measures, has been extensively documented in the broader misreporting literature (Bound *et al.* 2001; Meyer *et al.* 2015). However, it is important to emphasize that using home damage reports provided by other household members, as done in our analysis, does not fully eliminate concerns about the potential endogeneity of this variable. For instance, reverse causality—where individuals, including co-residing household members, with poorer health and lower life satisfaction are more likely to report weather-related home damage, and to do so inconsistently, as shown earlier in Subsection 4.1—remains a key source of endogeneity in self-reported measures. Moreover, although our empirical strategy accounts for time-invariant unobservable factors through individual fixed effects, time-varying unobservable factors that are correlated with self-reported damage may still influence the reports provided by other household members (Wooldridge 2010). Consequently, the estimates based on these alternative reports should not be interpreted as causal.

Furthermore, while this study sheds light on factors associated with inconsistent reporting of weather-related home damage among household members, it is beyond its scope to precisely identify the determinants of such misreporting. As noted earlier, this study does not assume ex ante which household member's report is more accurate. Doing so would require a dedicated study employing a different dataset with more objective and accurate measures of home damage, or alternative empirical strategies. This remains an important avenue for future research.

Similarly, although the findings suggest that self-reported weather-related home damage should not be treated as exogenous when assessing its impact on individual life outcomes, this study does not attempt to address the potential endogeneity of such reports. Further research is needed to identify appropriate methods for estimating the causal effects of weather-related home damage. One potential approach is to employ more accurate measures of damage, such as administratively reported data, geo-coded information, or satellite-based assessments (Guiteras *et al.* 2015; Donaldson & Storeygard 2016; Nguyen *et al.* 2023). Another widely adopted strategy is the use of instrumental variable techniques, as recommended in the misreporting literature (Meyer *et al.* 2015; DiTraglia & García-Jimeno 2019; Calvi *et al.* 2022; Gallagher 2023; Nguyen *et al.* 2024a). Some existing studies, for instance, have used exposure to local natural disasters as instruments for home damage (Baryshnikova & Pham 2019; Nguyen & Mitrou 2024a, 2025a).

6. Conclusion

This study pioneers the investigation of inconsistencies in self-reported weather-related home damage, identifying the determinants of within-household discrepancies and assessing the implications of using such measures in empirical analyses. It yields three key findings.

First, it documents a new pattern of substantial intra-household inconsistency in self-reported damage: in over half of the cases where one household member reports weather-related home damage, their co-residing relative does not. This finding is particularly notable given the familial closeness of the respondents and the shared living environment.

Second, household fixed-effects analyses indicate that a range of factors—including individual health, life satisfaction, local socio-economic conditions, and exposure to tropical cyclones—are systematically associated with both the likelihood of reporting damage and the probability of inconsistent reporting within households. Individuals in better health, with higher life satisfaction, or living in more socio-economically advantaged areas are less likely to report damage—whether consistently or inconsistently—than their household counterparts. In contrast, financial variables show no significant association with reporting behaviour.

Third, the findings suggest that reliance on more objective measures of weather-related home damage would significantly attenuate the estimated associations between such damage and individual outcomes such as health and life satisfaction.

These novel insights have important implications for future research. They challenge the common assumption of exogeneity often applied to self-reported damage measures and highlight the risk of biased inference when endogeneity is not properly addressed. The findings underscore the need for greater scrutiny of self-reported weather-related damage in survey-based studies and point to the value of incorporating administrative or geo-referenced data to improve the reliability of exposure measurement and the robustness of causal inference.

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Table 1: Self-reported weather-related home damage by relationship to other household members

	Individual				
	No		Yes		Total
	Number of observations	Row percentage (%)	Number of observations	Row percentage (%)	Number of observations
Relationship to individual	(1)	(2)	(3)	(4)	(5)
Panel A: Spouse					
No	127,002	*99.04*	1,226	***0.96***	128,228
Yes	1,226	***57.56***	904	*42.44*	2,130
Total	128,228	*98.37*	2,130	*1.63*	130,358
Panel B: Mother					
No	25,883	*99.11*	232	***0.89***	26,115
Yes	336	***69.42***	148	*30.58*	484
Total	26,219	*98.57*	380	*1.43*	26,599
Panel C: Father					
No	19,767	*99.07*	186	***0.93***	19,953
Yes	217	***68.45***	100	*31.55*	317
Total	19,984	*98.59*	286	*1.41*	20,270
Panel D: All other household members					
No	173,180	*98.98*	1,777	***1.02***	174,957
Yes	1,809	***61.43***	1,136	*38.57*	2,945
Total	174,989	*98.36*	2,913	*1.64*	177,902

Notes: Samples consist of matched co-residing individuals with no missing data on any variables included in the baseline model.

Table 2: Sample means of key covariates and outcomes by inconsistent reporting status

	Inconsistent reporting	Consistent reporting	Inconsistent - Consistent (1) - (2)
	(1)	(2)	(3)
Age (years)	42.416	44.181	-1.765***
Male [(a)]	0.484	0.483	0.000
ESB migrant [(a)]	0.093	0.093	0.000
NESB migrant [(a)]	0.098	0.115	-0.016***
Year 12 [(a)]	0.151	0.152	-0.001
Vocational or training qualification [(a)]	0.402	0.379	0.023***
Bachelor or higher [(a)]	0.167	0.213	-0.047***
Household size	3.286	3.233	0.053**
Homeowner [(a)]	0.662	0.727	-0.065***
Local area unemployment rate (%)	4.970	5.177	-0.206***
Local area SEIFA score	5.052	5.580	-0.528***
Major city [(a)]	0.514	0.625	-0.111***
Individual-level self-reported home damage [(a)]	0.496	0.007	0.489***
Household-level self-reported home damage [(a)]	0.504	0.007	0.498***
Mental health (standardized)	-0.216	0.009	-0.224***
Physical functioning (standardized)	-0.046	0.064	-0.110***
General health (standardized)	-0.139	0.008	-0.147***
Overall life satisfaction (standardized)	-0.052	0.068	-0.120***
Respondent's market income ($1,000)	41.467	43.691	-2.223**
Equivalised household disposable income ($1,000)	56.691	59.391	-2.700***
Observations	3,586	174,316	

Notes: Figures are sample means. The "inconsistent reporting" group comprises individuals whose reports of weather-related home damage in the past year differ from those of other household members, whereas the "consistent reporting" group includes individuals whose reports are consistent with those of other members of their household. [(a)] indicates a binary variable. Tests assess the statistical significance of differences between the sample means of the two groups. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 3: Determinants of (in)consistency in self-reported weather-related home damage

Relationship to individual:	Spouse				All other household members			
Outcome variable:	Individual "Yes", Spouse "Yes"	Individual "Yes", Spouse "No"	Individual "No", Spouse "Yes"	Individual ≠ Spouse	Individual "Yes", Others "Yes"	Individual "Yes", Others "No"	Individual "No", Others "Yes"	Individual ≠ Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	-0.01	-0.01	-0.02	-0.02	-0.00	0.01	0.00	0.01
	[0.01]	[0.02]	[0.02]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]
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]	[0.00]	[0.00]	[0.00]	[0.00]
Male	-0.02*	0.10**	-0.08*	0.02	-0.02	0.05	-0.03	0.03
	[0.01]	[0.04]	[0.04]	[0.02]	[0.02]	[0.04]	[0.04]	[0.04]
ESB migrant [(a)]	-0.05	0.01	0.15	0.14	-0.08	0.00	0.12	0.10
	[0.09]	[0.10]	[0.10]	[0.13]	[0.09]	[0.09]	[0.10]	[0.13]
NESB migrant [(a)]	-0.20**	-0.08	0.01	-0.04	-0.14*	-0.06	0.01	-0.03
	[0.09]	[0.10]	[0.10]	[0.15]	[0.07]	[0.09]	[0.09]	[0.14]
Year 12 [(b)]	0.00	-0.07	-0.03	-0.07	-0.06	-0.12	-0.10	-0.19
	[0.09]	[0.11]	[0.12]	[0.15]	[0.06]	[0.08]	[0.09]	[0.12]
Vocational or training qualification [(b)]	0.03	0.10	-0.15*	-0.03	0.00	0.12	-0.12*	0.00
	[0.07]	[0.08]	[0.08]	[0.11]	[0.05]	[0.07]	[0.07]	[0.10]
Bachelor degree or higher [(b)]	-0.05	-0.03	-0.22**	-0.19	-0.03	-0.04	-0.26***	-0.26**
	[0.08]	[0.10]	[0.10]	[0.14]	[0.07]	[0.08]	[0.08]	[0.12]
Number of household members	0.06*	0.01	0.02	0.03	0.02	0.03	-0.03	-0.02
	[0.04]	[0.03]	[0.03]	[0.06]	[0.03]	[0.03]	[0.03]	[0.05]
Homeowner	0.22**	-0.21**	-0.18*	-0.34**	0.18**	-0.28***	-0.13	-0.39***
	[0.10]	[0.10]	[0.10]	[0.17]	[0.07]	[0.08]	[0.09]	[0.14]

Relationship to individual:	Spouse				All other household members			
Outcome variable:	Individual "Yes", Spouse "Yes"	Individual "Yes", Spouse "No"	Individual "No", Spouse "Yes"	Individual ≠ Spouse	Individual "Yes", Others "Yes"	Individual "Yes", Others "No"	Individual "No", Others "Yes"	Individual ≠ Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local area unemployment rate	-0.02	-0.02	-0.02	-0.04	-0.05	-0.03	-0.02	-0.04
	[0.06]	[0.05]	[0.05]	[0.09]	[0.05]	[0.05]	[0.05]	[0.08]
Local area SEIFA score	-0.08***	-0.06***	-0.06***	-0.10***	-0.08***	-0.06***	-0.06***	-0.10***
	[0.02]	[0.02]	[0.02]	[0.03]	[0.02]	[0.01]	[0.02]	[0.03]
Major city	-0.08	-0.33***	-0.34***	-0.61***	-0.11	-0.48***	-0.42***	-0.82***
	[0.12]	[0.11]	[0.11]	[0.19]	[0.11]	[0.10]	[0.11]	[0.18]
Observations	127,906	128,228	128,228	130,358	174,316	174,957	174,989	177,902
N of unique households	19,939	20,037	20,037	20,109	21,907	22,030	22,026	22,098
Mean dependent variable (×100)	0.71	0.96	0.96	1.88	0.65	1.02	1.03	2.02

Notes: Each column reports results from a separate household fixed effects OLS regression model, using Equation (1). The outcome variable for each model is indicated in the first two rows of the table. Results (coefficients and standard errors) are multiplied by 100 for aesthetic purposes. Other explanatory variables include survey wave dummies, survey month dummies, and state/territory dummies. [a] and [b] denotes “Australian-born” and “Under Year 12” as the comparison group, respectively. Robust standard errors are clustered at the household level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 4: Association between health, life satisfaction, and financial factors and (in)consistency in self-reported weather-related home damage

Binary outcome variable:	Individual "Yes", Others "Yes"	Individual "Yes", Others "No"	Individual "No", Others "Yes"	Individual ≠ Others
By additional explanatory variable	(1)	(2)	(3)	(4)
Panel A: Mental health	-0.13***	-0.22***	-0.13***	-0.30***
	[0.03]	[0.03]	[0.03]	[0.04]
Observations	152,299	152,756	152,804	155,241
N of unique households	20,364	20,426	20,446	20,518
Panel B: Physical functioning	-0.15***	-0.13***	-0.04	-0.15***
	[0.03]	[0.03]	[0.03]	[0.05]
Observations	151,476	151,928	151,981	154,401
N of unique households	20,358	20,421	20,441	20,512
Panel C: General health	-0.12***	-0.14***	-0.03	-0.16***
	[0.03]	[0.03]	[0.03]	[0.04]
Observations	151,540	151,995	152,043	154,464
N of unique households	20,347	20,407	20,426	20,499
Panel D: Overall life satisfaction	-0.04	-0.17***	-0.13***	-0.27***
	[0.03]	[0.03]	[0.03]	[0.05]
Observations	159,891	160,389	160,438	163,020
N of unique households	20,748	20,814	20,832	20,905
Panel E: Individual market income	-0.02	0.06	0.08	0.13
	[0.03]	[0.07]	[0.06]	[0.09]
Observations	159,949	160,446	160,495	163,078
N of unique households	20,749	20,815	20,833	20,906
Panel F: Equivalised household disposable income	-0.03	-0.01	0.03	0.01
	[0.04]	[0.04]	[0.05]	[0.08]
Observations	159,949	160,446	160,495	163,078
N of unique households	20,749	20,815	20,833	20,906

Notes: Results in each column and panel are derived from separate household fixed effects OLS regression models, specified similarly to Equation (1), with the inclusion of an additional explanatory variable as indicated in each panel, introduced with a one-year lag. The outcome variable for each model is indicated in the first row of the table. For aesthetic purposes, results (coefficients and standard errors) are multiplied by 100 for health and life satisfaction outcomes, and by 10,000 for financial outcomes. Other explanatory variables include age, age squared, gender, migrant status, education, household size, homeownership status, local area socio-economic conditions, major city dummy, survey wave dummies, survey month dummies, and state/territory dummies. Robust standard errors are clustered at the household level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 5: Association between own and spouse's health and life satisfaction and (in)consistency in self-reported weather-related home damage

Outcome variable:	Individual "Yes", Spouse "Yes"		Individual "Yes", Spouse "No"		Individual "No", Spouse "Yes"		Individual ≠ Spouse	
By gender:	Female	Male	Female	Male	Female	Male	Female	Male
By additional explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Mental health								
Own mental health	-0.16***	-0.15***	-0.13**	-0.30***	-0.08	-0.17***	-0.19**	-0.45***
	[0.05]	[0.05]	[0.05]	[0.07]	[0.06]	[0.06]	[0.08]	[0.09]
Spouse's mental health	-0.16***	-0.16***	-0.19***	-0.08	-0.29***	-0.13**	-0.45***	-0.20***
	[0.05]	[0.05]	[0.06]	[0.06]	[0.06]	[0.05]	[0.09]	[0.08]
Observations	55,594	55,323	55,655	55,476	55,741	55,392	56,590	56,313
No of unique households	17,524	17,510	17,522	17,516	17,530	17,509	17,634	17,620
Panel B: Physical functioning								
Own physical functioning	-0.18***	-0.17***	-0.09	-0.16**	-0.06	-0.02	-0.13	-0.18**
	[0.06]	[0.06]	[0.06]	[0.07]	[0.06]	[0.06]	[0.08]	[0.09]
Spouse's physical functioning	-0.18***	-0.18***	-0.06	-0.07	-0.14**	-0.08	-0.19**	-0.13
	[0.06]	[0.06]	[0.06]	[0.06]	[0.07]	[0.06]	[0.09]	[0.08]
Observations	54,994	54,731	55,054	54,890	55,147	54,798	55,983	55,713
No of unique households	17,475	17,459	17,475	17,468	17,484	17,460	17,587	17,571
Panel C: General health								
Own general health	-0.15***	-0.14***	-0.09*	-0.23***	0.10*	-0.05	0.01	-0.26***
	[0.05]	[0.05]	[0.05]	[0.06]	[0.05]	[0.06]	[0.07]	[0.08]
Spouse's general health	-0.14***	-0.15***	-0.07	0.09	-0.23***	-0.08*	-0.28***	0.00
	[0.05]	[0.05]	[0.06]	[0.05]	[0.06]	[0.05]	[0.08]	[0.07]
Observations	55,055	54,792	55,114	54,944	55,201	54,859	56,038	55,769
No of unique households	17,459	17,445	17,458	17,451	17,465	17,445	17,566	17,552
Panel D: Overall life satisfaction								
Own life satisfaction	-0.02	-0.06	-0.16***	-0.15**	-0.14**	-0.06	-0.28***	-0.20**
	[0.05]	[0.06]	[0.06]	[0.07]	[0.07]	[0.06]	[0.09]	[0.09]
Spouse's life satisfaction	-0.05	-0.04	-0.07	-0.12*	-0.15**	-0.17***	-0.20**	-0.27***
	[0.06]	[0.05]	[0.06]	[0.07]	[0.07]	[0.06]	[0.09]	[0.09]
Observations	58,647	58,341	58,717	58,507	58,803	58,421	59,717	59,409
No of unique households	17,968	17,953	17,967	17,957	17,972	17,953	18,081	18,066

Notes: Results in each column and panel are derived from separate household fixed effects OLS regression models, specified similarly to Equation (1), with the inclusion of two additional explanatory variables as indicated in each panel, introduced with a one-year lag. The outcome variable for each model is indicated in the first row of the table. Results (coefficients and standard errors) are multiplied by 100 for aesthetic purposes. Other explanatory variables include age, age squared, migrant status, education, household size, homeownership status, local area socio-economic conditions, major city dummy, survey wave dummies, survey month dummies, and state/territory dummies. Robust standard errors are clustered at the household level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 6: Determinants of weather-related home damage and inconsistency in self-reporting

Relationship between pairs:	Couples		Household members	
Outcome variable:	Home damage	Individual ≠ Spouse	Home damage	Individual ≠ others
Variable	(1)	(2)	(3)	(4)
Age	-0.03*	-0.02	-0.00	0.01
	[0.02]	[0.03]	[0.01]	[0.01]
Age squared	0.00	0.00	-0.00	-0.00
	[0.00]	[0.00]	[0.00]	[0.00]
Male	-0.13**	0.02	-0.07	0.03
	[0.06]	[0.02]	[0.05]	[0.04]
ESB migrant [(a)]	0.17	0.14	0.09	0.10
	[0.14]	[0.13]	[0.13]	[0.13]
NESB migrant [(a)]	-0.15	-0.04	-0.09	-0.03
	[0.13]	[0.15]	[0.12]	[0.14]
Year 12 [(b)]	0.03	-0.07	-0.14	-0.19
	[0.15]	[0.15]	[0.11]	[0.12]
Vocational or training qualification [(b)]	-0.11	-0.03	-0.12	0.00
	[0.11]	[0.11]	[0.09]	[0.10]
Bachelor degree or higher [(b)]	-0.22*	-0.19	-0.25**	-0.26**
	[0.13]	[0.14]	[0.10]	[0.12]
Number of household members	0.09*	0.03	-0.02	-0.02
	[0.05]	[0.06]	[0.04]	[0.05]
Homeowner	0.06	-0.34**	0.05	-0.39***
	[0.12]	[0.17]	[0.11]	[0.14]
Local area unemployment rate	-0.01	-0.02	-0.03	-0.01
	[0.08]	[0.09]	[0.07]	[0.08]
Local area SEIFA score	-0.13***	-0.10***	-0.13***	-0.10***
	[0.02]	[0.03]	[0.02]	[0.03]
Major city	-0.36**	-0.60***	-0.46***	-0.81***
	[0.15]	[0.19]	[0.15]	[0.18]
Exposure to any cyclone within 100 km	1.59***	1.07**	1.64***	1.38***
	[0.39]	[0.45]	[0.39]	[0.42]
Observations	130,358	130,358	177,902	177,902
Number of unique households	20,109	20,109	22,098	22,098
Mean of dependent variable (x100)	1.63	1.88	1.66	2.02
Proportion affected (%)	3.25	3.25	3.17	3.17

Notes: Results in each column are derived from separate household fixed effects OLS regression models, specified similarly to Equation (1), with exposure to any cyclone within 100 km included as an additional explanatory variable. The outcome variable for each model is indicated in the second row of the table. Results (coefficients and standard errors) are multiplied by 100 for aesthetic purposes. Other explanatory variables include survey wave dummies, survey month dummies, and state/territory dummies. [(a)] and [(b)] denotes "Australian-born" and "Under Year 12" as the comparison group, respectively. "Proportion affected (%)" refers to the percentage of the sample that experienced exposure to at least one cyclone in the 12 months preceding the survey date. Robust standard errors are clustered at the household level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 7: Implications of using inconsistently self-reported weather-related home damage

Relationship between pairs:	Couples		Household members	
Home damage reported by:	Own	Spouse	Own	Others
By outcome variable	(1)	(2)	(3)	(4)
Panel A: Mental health				
Home damage	-0.06***	-0.02	-0.05***	-0.02
	[0.02]	[0.02]	[0.01]	[0.01]
Observations	129,985	129,985	177,330	177,330
No of unique individuals	16,971	16,971	24,846	24,846
Panel B: Physical functioning				
Home damage	-0.04**	0.03*	-0.03**	0.02
	[0.02]	[0.02]	[0.01]	[0.01]
Observations	129,209	129,209	176,255	176,255
No of unique individuals	16,936	16,936	24,795	24,795
Panel C: General health				
Home damage	-0.04***	-0.00	-0.04***	-0.01
	[0.01]	[0.01]	[0.01]	[0.01]
Observations	129,365	129,365	176,501	176,501
No of unique individuals	16,952	16,952	24,817	24,817
Panel D: Overall life satisfaction				
Home damage	-0.03*	-0.00	-0.03**	-0.00
	[0.02]	[0.02]	[0.02]	[0.01]
Observations	130,325	130,325	177,841	177,841
No of unique individuals	16,980	16,980	24,869	24,869
Panel E: Individual market income				
Home damage	-1.00	-0.05	-0.79	-0.22
	[1.14]	[0.71]	[0.88]	[0.58]
Observations	130,250	130,250	177,696	177,696
No of unique individuals	16,936	16,936	24,816	24,816
Panel F: Equivalised household disposable income				
Home damage	-0.64	-0.78	-0.66	-1.01
	[0.97]	[0.96]	[0.81]	[0.81]
Observations	130,250	130,250	177,696	177,696
No of unique individuals	16,936	16,936	24,816	24,816

Notes: Results in each panel and column are derived from separate individual fixed effects OLS regressions. The outcome variable for each model is specified in the corresponding panel. Weather-related home damage is self-reported by either the individual or the relevant co-residing household member, as indicated in the first two rows of the table. Other explanatory variables include age, age squared, gender, migrant status, education, household size, homeownership status, local area socio-economic conditions, major city dummy, survey wave dummies, survey month dummies, and state/territory dummies. Robust standard errors are clustered at the individual level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix tables and figures

for refereeing purposes and to be published online

Appendix Table A1: Variable description and summary statistics

Variable	Description	Mean	S.D.
Age	The respondent's age at the survey time (years)	44.146	18.36
Male	Dummy variable: = 1 if the individual is male; 0 otherwise	0.483	0.50
ESB migrant	Dummy variable: = 1 if the individual was born overseas in an English-Speaking Background (ESB) country; 0 otherwise	0.093	0.29
NESB migrant	Dummy variable: = 1 if the individual was born overseas in a Non-English-Speaking Background (NESB) country; 0 otherwise	0.114	0.32
Year 12	Dummy: = 1 if the individual completes Year 12; 0 otherwise	0.152	0.36
Vocational or training qualification	Dummy: = 1 if the individual has a vocational or training qualification; 0 otherwise	0.380	0.49
Bachelor or higher	Dummy: = 1 if the individual has a bachelor degree or higher; 0 otherwise	0.212	0.41
Household size	Number of household members	3.234	1.34
Homeowner	Dummy variable: = 1 if the individual resides in a home that is owned outright or mortgaged; 0 otherwise	0.726	0.45
Local area unemployment rate	Yearly unemployment rate at the individual's residing local government area (%)	5.173	1.12
Local area SEIFA decile	Socio-Economic Indexes for Areas (SEIFA) decile at the individual's residing local government area; higher values indicate greater socio-economic advantage	5.569	2.83
Major city	Dummy variable: = 1 if the individual lives in a major city; 0 otherwise	0.622	0.48
Individual-level 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?"; 0 otherwise	0.016	0.13
Household-level home damage	Dummy variable: = 1 if a majority (i.e., ≥50%) of the other responding household members—excluding the individual in question—report weather-related home damage; 0 otherwise	0.017	0.13
Mental health	Short Form (SF)-36 mental health; a higher score indicating better health; standardized	0.004	0.99
Physical health	Short Form (SF)-36 physical functioning; a higher score indicating better health; standardized	0.061	0.96
General health	Short Form (SF)-36 summary score; a higher score indicating better health; standardized	0.005	0.98
Overall life satisfaction	Responses to the question "All things considered, how satisfied are you with your life?"; a higher score indicating greater life satisfaction; standardized	0.066	0.93
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)	43.646	61.09
Equivalised household disposable income	Household disposable income from all sources, normalized by squared root of household size ($1,000, financial year, 2010 price)	59.337	60.04
Any cyclone within 100 km	Dummy variable: = 1 if the individual's residing postcode was within 100 km of any cyclone's eye in the previous year; 0 otherwise	0.032	0.18

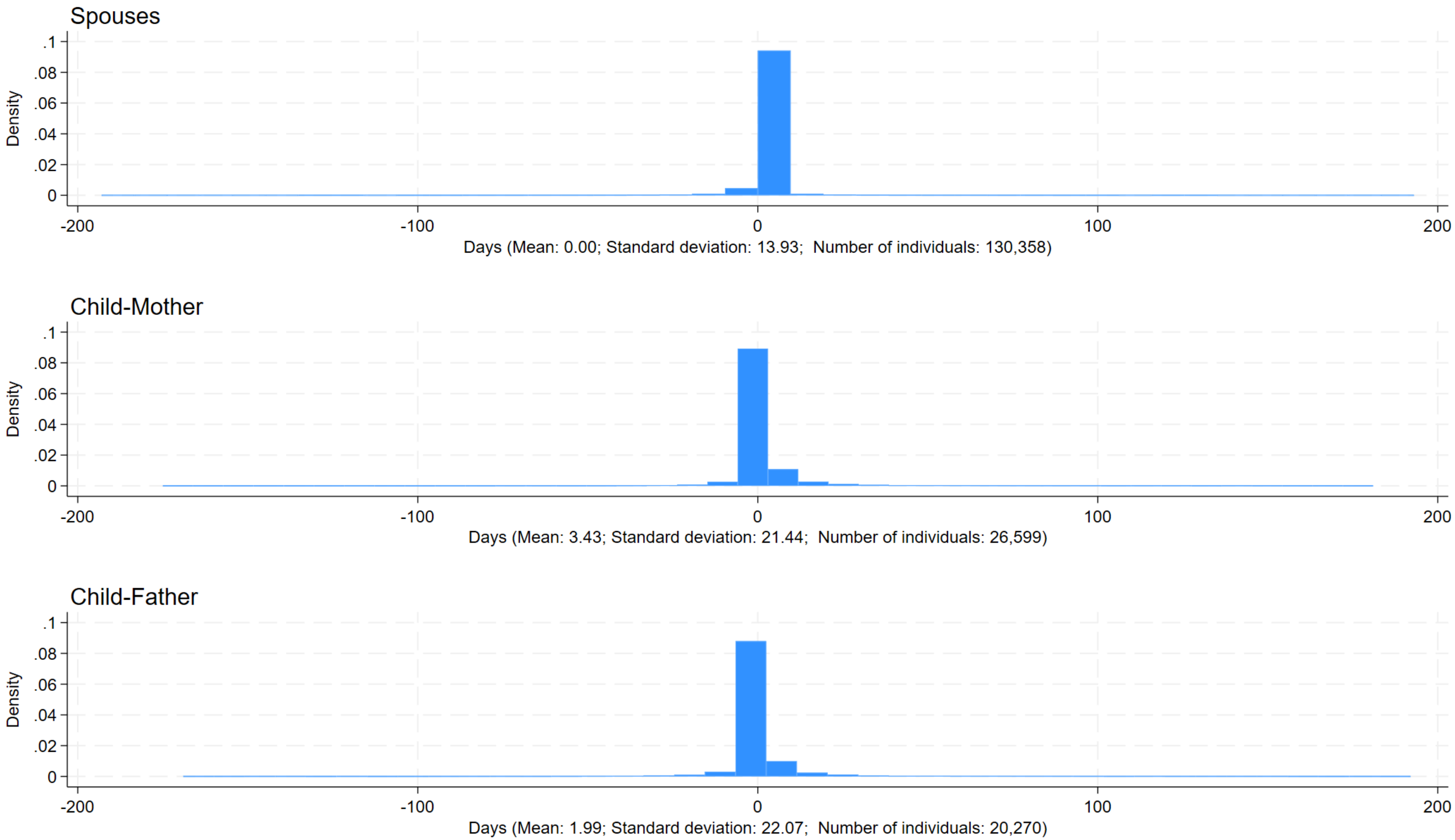
Notes: Statistics are based on an analytical sample of 177,902 individuals included in the regression analysis of any inconsistency in self-reported home damage between household members.

Appendix Table A2: Association between health, life satisfaction, and financial factors and (in)consistency in self-reported weather-related home damage - Spouse pairs

Binary outcome variable:	Individual "Yes", Spouse "Yes"	Individual "Yes", Spouse "No"	Individual "No", Spouse "Yes"	Individual ≠ Spouse
By additional explanatory variable	(1)	(2)	(3)	(4)
Panel A: Mental health	-0.15***	-0.25***	-0.13***	-0.33***
	[0.03]	[0.04]	[0.04]	[0.05]
Observations	116,021	116,285	116,274	118,162
N of unique households	18,758	18,812	18,830	18,900
Panel B: Physical functioning	-0.17***	-0.13***	-0.05	-0.15***
	[0.04]	[0.04]	[0.04]	[0.05]
Observations	115,402	115,669	115,659	117,536
N of unique households	18,758	18,814	18,830	18,900
Panel C: General health	-0.13***	-0.15***	-0.01	-0.14***
	[0.03]	[0.04]	[0.03]	[0.05]
Observations	115,442	115,705	115,693	117,570
N of unique households	18,744	18,798	18,813	18,886
Panel D: Overall life satisfaction	-0.05	-0.19***	-0.14***	-0.29***
	[0.04]	[0.04]	[0.04]	[0.06]
Observations	120,719	120,996	120,992	122,967
N of unique households	19,024	19,085	19,096	19,167
Panel E: Individual market income	-0.06*	0.04	0.08	0.11
	[0.03]	[0.07]	[0.06]	[0.10]
Observations	120,750	121,027	121,023	122,998
N of unique households	19,024	19,085	19,096	19,167
Panel F: Equivalised household disposable income	-0.04	0.02	0.03	0.04
	[0.05]	[0.05]	[0.05]	[0.08]
Observations	120,750	121,027	121,023	122,998
N of unique households	19,024	19,085	19,096	19,167

Notes: Results in each column and panel are derived from separate household fixed effects OLS regression models, specified similarly to Equation (1), with the inclusion of an additional explanatory variable as indicated in each panel, introduced with a one-year lag. The outcome variable for each model is indicated in the first row of the table. For aesthetic purposes, results (coefficients and standard errors) are multiplied by 100 for health and life satisfaction outcomes, and by 10,000 for financial outcomes. Other explanatory variables include age, age squared, gender, migrant status, education, household size, homeownership status, local area socio-economic conditions, major city dummy, survey wave dummies, survey month dummies, and state/territory dummies. Robust standard errors are clustered at the household level and reported in parentheses. The symbol * denotes statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Appendix Figure A1: Differences in survey time between responding pairs



Notes: This figure presents the distribution of differences in survey dates (measured in days) between responding household member pairs within the same survey wave. Summary statistics—including the mean, standard deviation, and number of observations—for each pair type are reported in the x-axis label of the corresponding panel.