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Natural Disasters and Mental Health: A Quantile Approach *

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Abstract

Mental health has been recently declared a global priority by the World Bank and World Health Organization. This article investigates heterogeneity in the effect of experiencing natural disasters on mental health. Using population representative longitudinal data from Australia, we find that home owners generally show a reduction in mental health score after a disaster. While the average effect for those that do not own a house is zero, the quantile approach reveals that there is a strong negative effect in the lowest two quantiles of the distribution for the non-owners. The results suggest that policies targeted at home owners and the lowest mental health non-owners (rather than only at the economically poorest) would help mitigate mental health consequences attributable to natural disaster exposure.

Keywords: quantile treatment effects; mental health; disasters; home owners; panel data.

JEL Codes: C21 · C23 · I31 · Q54 · R2

1 Introduction

Natural disasters such as earthquakes, hurricanes, tornadoes, floods or fires, threaten the lives of millions of people every year. Anyone experiencing a disaster may incur measurable financial costs, such as loss of home and possessions, and potentially life-long non-monetary

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costs. Facing the danger of death or physical injury, the loss of loved ones, and financial stressors, can spark depression, generalized anxiety and a plethora of other emotional and physical health problems. These effects may reduce individuals' labor supply and productivity, and also increase the risk of falling into poverty (Das et al., 2008).

The literature investigating how natural disasters affect mental health is very limited. Obradovich et al. (2018) find that exposure to tropical cyclones, like Katrina, on average worsen mental health using. Several studies have noted a negative effect at means of a particular event, a certain type of disaster, or extreme environmental events on subjective wellbeing, life satisfaction, and happiness. Carroll et al. (2009) find that droughts in Australia decrease life satisfaction in rural areas. Luechinger and Raschky (2009) document a negative impact of flood disasters on life satisfaction and subjective wellbeing in repeated cross-sections in 16 European countries. Rehdanz et al. (2015) find a negative effect of the Fukushima disaster on subjective wellbeing. Interestingly, not all papers find the disaster effect to be negative. Yamamura (2012) concludes that the survivors of the Kobe earthquake experienced a long-lasting positive effect on subjective wellbeing.

We add to the literature by studying the effects of all types of disasters in Australia on mental health. In particular, we explore whether the effect of experiencing a natural disaster varies along the mental health distribution: while some individuals may end up with mental illness after a disaster, are there people in the mental health distribution who would experience no effect, or even a positive consequence? Furthermore, there may be heterogeneity of the disaster effect across home ownership status as well as across the mental health distribution. Owning a home is a large investment and is generally associated with higher income, status, and stability. However, in the aftermath of a disaster that damages the home, this could also be a source of higher costs, higher distress, and larger losses. Renters, on the other hand, are known to have greater mobility and have less financial and emotional investment in a home.

The heterogeneity of the effect of disasters on mental health is captured using a population-representative longitudinal survey conducted between 2009 and 2016. Specifically, we use a panel quantile model with fixed effects and, using several methods, evaluate the effects of experiencing a disaster on different quantiles of mental health for home owners and non-owners separately. The results are similar across all specifications and reveal that experiencing damage from natural disasters generally has a negative effect on mental health scores. While the average effect on non-owners is zero, the quantile methods reveal that there is a strong negative effect in the lowest two quantiles of the distribution of the non-owners.

2 Data

Our data is from the Household, Income and Labour Dynamics in Australia (HILDA) survey.[4] This annual household-based panel study collects information on socioeconomic characteristics, wellbeing, and family circumstances. Information related to weather-related disaster events such as floods, bush fires and cyclones are available from wave 9 onwards. Therefore, our analysis is based on HILDA data waves 9-16 in 2009-2016.

We are primarily interested in individuals' mental wellbeing, which we measure using the Mental Health Component Summary Score (MCS) constructed from the Short Form 36 measure in HILDA. This is an internationally standardized measure based on 8 dimensions of the individual's mental health status such as emotional role functioning, social role functioning, and mental health. The scale ranges from 0 to 100 with lower scores indicating lower mental health. Our main independent variable indicates whether a weather-related disaster (e.g., flood, bush fire, cyclone) damaged or destroyed a person's home during the past 12 months. For heterogeneity across home ownership we split the sample into home owners and renters.

Table 1 reports the means for the mental health score and the main control variables, while Table 2 shows the summary statistics across the waves. People who experienced a disaster have lower education, lower income and poor health, and drink and smoke more. Generally, home owners have higher education and income and better health, but drink more alcohol daily.

Figure 1 shows the empirical density functions of mental health scores for different population groups. The distribution for individuals that were affected by disaster is flattened and has thicker tails (Figure 1(a)). The distributions for owners and renters affected by

[4] We use the general HILDA release in this study.

disasters are also different (Figure 1(b)).

3 Methodology

The classical panel fixed effects model that relates mental health scores to experiencing damage from a natural disaster is

$$MCS_{it} = \beta \times Damage_{it} + X_{it}^{'}\gamma + \mu_i + \mu_t + +\mu_s + U_{it} \quad (1)$$

where the outcome variable, MCS_{it}, is the mental health score of individual i in year t. $Damage_{it}$, our variable of interest, indicates whether individual i's house has been damaged by a natural disaster in year t. X_{it} is a vector of covariates, such as age, the square of age, household income, marital status, tertiary education, living location, disability, health status, smoking, drinking, and occupation. μ_i, μ_s and μ_t are unobservable individual, state and year fixed effects, respectively, that address any potential endogeneity in the variable of interest, $Damage_{it}$. U_{it} is the unobservable error term.

The quantile fixed effects approach of Eq.(1) is:

$$Q_{MCS_{it}}(\tau_j|Damage_{it}, X_{it}) = \beta(\tau_j) \times Damage_{it} + X_{it}^{'}\gamma(\tau_j) + \mu_i(\tau_j) + \mu_t(\tau_j) + \mu_s(\tau_j) \quad (2)$$

for all quantiles $\tau_j \in (0, 1)$. The effect of disaster damage on the mental health score of individual i in year t is captured by the coefficient $\beta(\tau_j)$ and $\gamma(\tau_j)$ measures the effects of a change in other covariates on the mental health score as functions of quantiles.

To investigate heterogeneity in mental health score changes in response to damage from disasters across the quantiles, Eq.(2), we apply several methods. First, as a benchmark, we use the quantile random effects (Pooled QR) of Koenker and Bassett, Jr. (1978) which assumes no correlation between the individual effects and the regressors. As it is unlikely that this assumption is satisfied, we control for the correlation between individual effects and the regressors with a number of alternatives. The fixed effects quantile regression (QRFE) of Kato et al. (2012) with subsamples allows us to control for individual effects, but suffers from the incidental parameter problem. We note that the proof of consistency for QRFE by Kato et al. (2012) requires a large time series dimension T and the ratio N/T to go to zero. In our application, we have a large $N = 22,201$ and small $T = 8$, which results in too many dummies and renders the method inconsistent. We also estimate the panel quantile treatment effect with IV (IV-QTE) of Abadie et al. (2002), which uses an instrumental variable to remedy the omitted fixed effects bias. While this bypasses the incidental parameter problem by omitting the effects, the method does not include year and state effects. Our final alternative is Powell's (2016) GMM approach for quantile panel data with fixed effects.[5] As shown in his paper, Powell's methodology yields consistent quantile estimates of $MCS_{it}|Damage_{it}, X_{it}$ even for short time series dimension T ($T = 8$ in our study).

A possible threat to identification is that our main regressor could be endogenous. Specifically, this regressor could be endogenous due to reverse causality: poor mental health could affect how well the home is maintained and put the house more at risk of damage from a disaster. Similarly to Yang (2008), we instrument for home damage due to a disaster with events whose occurrence is plausibly exogenous to the mental health of any given individual: the occurrence of natural disasters in the state during a given year. It is highly likely that the occurrence of weather disasters is exogenous to mental health, as it is caused purely by weather conditions and not the individual characteristics or situation. The IV data comes from EM-DAT - The Emergency Events Database. Unfortunately, we cannot use instruments with a more precise geographical location as our mental health dataset does not have the geolocation of the individuals other than the state.

4 Results

Table 3 presents the estimated effects of experiencing damage from disaster on mental health for the full sample. The first important result is the existence of heterogeneity in the effects of disaster across the distribution of mental health. On average, in the full sample, the naïve Fixed Effects at mean (not shown in tables) shows that experiencing a damaging natural

[5] While the paper by Powell (2016) presents the estimation for the case of IV, for an exogenous regressor the method collapses to a simple method of moments. We use the Markov Chain Monte Carlo algorithm (MCMC) and adjust for clustering at the individual level.

disaster in the previous 12 months is associated with a 0.37 drop in the mental health score at a 10% significance level. This result is in line with Carroll et al. (2009); Luechinger and Raschky (2009); Rehdanz et al. (2015), and Obradovich et al. (2018). Our quantile results reveal heterogeneity in the magnitude of the effects of disasters across the mental health distribution. In general, the full sample effect is significantly negative or insignificant across all of the quantile methods.

An important threat to identification is that the damage to the house due to a disaster may not be exogenous (see Section 3). The occurrence of a natural disaster in a given year and in a given state passes the first stage diagnostic tests (Table A1) as a good IV. The IV-QTE/QRPD estimates (Rows C and E in Table 3) show that the effect of experiencing a natural disaster in the past 12 months is mostly negative across quantiles.

The second important result is heterogeneity across home ownership status. Tables 4 and 5 split the sample and reveal that home owners' and non-owners' mental health responds differently to the effect of disaster damage. The results show that the negative effect of disaster damage in the full sample is mainly driven by home owners. Home owners experience a negative effect on mental health in all quantiles across all methods.

The effect on non-owners is heterogenous across quantiles and specifications, but all methods suggest that the effect is negative in the bottom two quantiles of the distribution. A plausible explanation that the lower quantiles suffer a negative effect is that people who are already struggling with mental health spiral down more into negative patterns after facing a damaging experience. In the 50^{th} and 75^{th} percentiles, for example, QRFE in Row B of Table 5, shows positive effects. The possible average positive effects on happiness have been previously noted in Yamamura (2012). This is in line with the story that renters could move from a damaged home faster, and could feel the "life after near-death effect" subsequent to experiencing disasters by re-thinking what is truly important and coming to appreciate what they value most in life. In the top quantile the effect becomes negative again in all specifications, except QRFE. The people in the upper quantile were optimistic but had, perhaps, unrealistic expectations and attitudes towards life which were shattered by the damaging disaster. These significant effects are canceled out and do not come through in the average fixed effects regression for the non-owners ($\hat{\beta} = 0.006$, insignificant).

5 Conclusion

We have shown that damage from experience of a natural disaster has a negative effect on mental health on average, and importantly, that the effect is different in different parts of the mental health distribution. Using the quantile panel treatment model we find that homeowners suffer a negative effect on mental health across all quantiles, while people who do not own a home possibly experience a positive effect for the upper middle quantiles. These findings provide empirical evidence to help identify the population groups that are severely affected by disasters in terms of mental health. Unlike policies for economic impact that are usually targeted to the poorest, addressing the mental health impact of disasters requires policies targeted at home owners and those with the lowest and highest mental health status.

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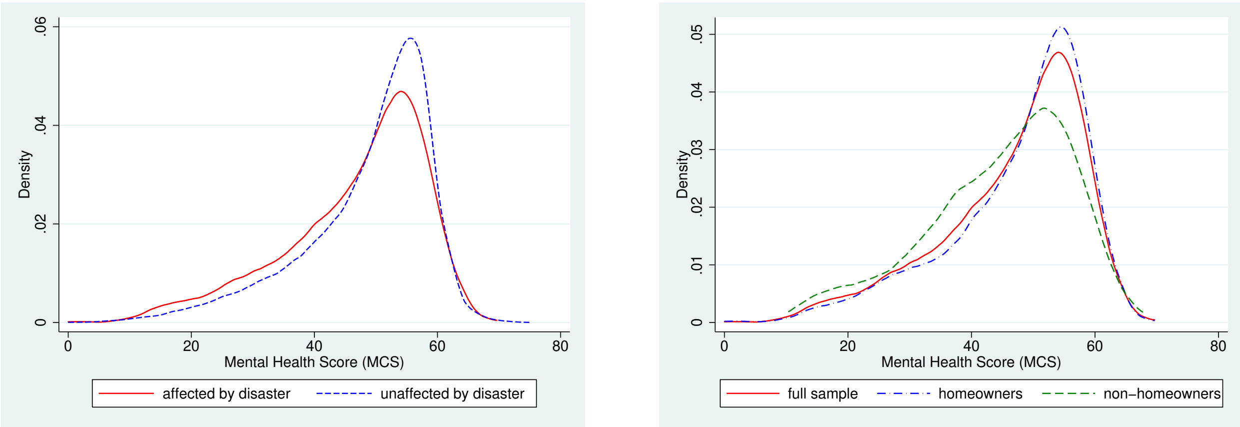
Figures

Figure 1: Distribution of Mental Health Score



(a) Full sample

(b) Individuals Affected by Disasters

Note. Figure 1(a) shows the MCS distribution of individuals who reported that their houses were damaged or destroyed by a weather related disaster (flood, bushfire, cyclone) and those whose houses were not affected by a disaster. Figure 1(b) represents the MCS of disaster victims using full, home owner and non-owner samples.

Tables

Table 1: Descriptive Statistics

Variables	**Total**	**Disaster Experience**			**Home Ownership**		
		No	**Yes**	**Diff**	**Owner**	**Renter**	**Diff**
Mental Health Score (MCS)	48.69	48.659	46.625	2.034***	46.371	49.572	-3.201***
	(10.434)	(10.526)	(11.467)	(0.276)	(11.267)	(9.941)	(0.056)
Household income (1,000)	101.213	117.078	112.263	4.815*	76.124	113.052	-36.928***
	(98.672)	(109.421)	(120.098)	(2.839)	(66.798)	(107.338)	(0.366)
Age	44.013	44.956	43.823	1.133***	36.724	46.92	-10.197***
	(18.657)	(18.764)	(17.745)	(0.42)	(16.562)	(18.513)	(0.078)
Marital status	0.482	0.483	0.458	0.025**	0.246	0.583	-0.337***
	(0.5)	(0.5)	(0.498)	(0.012)	(0.431)	(0.493)	(0.002)
Tertiary education	0.218	0.247	0.205	0.042***	0.185	0.234	-0.049***
	(0.413)	(0.431)	(0.404)	(0.01)	(0.389)	(0.424)	(0.002)
Excellent or very good health	0.473	0.473	0.407	0.066***	0.447	0.483	-0.036***
	(0.499)	(0.499)	(0.491)	(0.012)	(0.497)	(0.5)	(0.003)
Long term health condition	0.272	0.28	0.342	-0.062***	0.28	0.268	0.012***
	(0.445)	(0.449)	(0.475)	(0.011)	(0.449)	(0.443)	(0.002)
Drinks alcohol daily	0.066	0.065	0.073	-0.008	0.046	0.075	-0.03***
	(0.249)	(0.247)	(0.261)	(0.006)	(0.209)	(0.264)	(0.001)
Smokes daily	0.152	0.148	0.23	-0.082***	0.278	0.11	0.168***
	(0.359)	(0.355)	(0.421)	(0.01)	(0.448)	(0.313)	(0.002)

Note. Standard deviations and standard errors are reported in parenthesis, $^{*}p < 10\%,^{**}p < 5\%,^{***}p < 1\%$

Table 2: Descriptive Statistics Across Waves

	Mean							
Variable	**wave 9**	**wave 10**	**wave 11**	**wave 12**	**wave 13**	**wave 14**	**wave 15**	**wave 16**
Mental Health Score (MCS)	49.08	48.683	48.898	48.915	48.889	48.466	48.123	48.023
	(10.209)	(10.263)	(10.262)	(10.36)	(10.522)	(10.743)	(10.838)	(10.93)
Damage	0.014	0.018	0.031	0.015	0.013	0.007	0.017	0.012
	(0.116)	(0.133)	(0.174)	(0.121)	(0.112)	(0.083)	(0.128)	(0.107)
Home owner	0.714	0.71	0.694	0.695	0.69	0.69	0.687	0.682
	(0.452)	(0.454)	(0.461)	(0.46)	(0.463)	(0.462)	(0.464)	(0.466)
Household income (1,000)	103.753	106.321	110.681	115.372	118.474	122.661	125.454	127.819
	(89.116)	(95.523)	(99.284)	(104.208)	(107.279)	(115.894)	(120.686)	(130.83)
Age	43.783	43.767	44.054	44.233	44.263	44.509	44.705	44.979
	(18.757)	(18.857)	(18.834)	(18.899)	(18.977)	(19.039)	(19.109)	(19.144)
Marital status	0.469	0.463	0.47	0.469	0.465	0.464	0.462	0.46
	(0.499)	(0.499)	(0.499)	(0.499)	(0.499)	(0.499)	(0.499)	(0.498)
Tertiary education	0.211	0.215	0.229	0.236	0.24	0.245	0.251	0.255
	(0.408)	(0.411)	(0.42)	(0.425)	(0.427)	(0.43)	(0.433)	(0.436)
Excellent or very good health	0.502	0.463	0.476	0.473	0.482	0.465	0.451	0.461
	(0.5)	(0.499)	(0.499)	(0.499)	(0.5)	(0.499)	(0.498)	(0.499)
Long term health condition	0.287	0.271	0.274	0.272	0.301	0.288	0.288	0.278
	(0.452)	(0.444)	(0.446)	(0.445)	(0.459)	(0.453)	(0.453)	(0.448)
Drinks alcohol daily	0.074	0.07	0.068	0.065	0.063	0.061	0.062	0.063
	(0.262)	(0.256)	(0.252)	(0.247)	(0.243)	(0.239)	(0.241)	(0.243)
Smokes daily	0.163	0.165	0.155	0.147	0.143	0.146	0.14	0.143
	(0.369)	(0.371)	(0.362)	(0.354)	(0.35)	(0.353)	(0.347)	(0.35)
Observations	11,028	11,705	14,959	15,005	15,010	15,260	15,091	15,864

Note. Standard deviations and standard errors are reported in parenthesis, $^{*}p < 10\%,^{**}p < 5\%,^{***}p < 1\%$

Table 3: Estimates of the Disaster Effect on Mental Health Score: Full Sample

A-Pooled QR	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-1.895***	-1.715***	-0.969***	-0.541***	-0.384*
	(0.619)	(0.398)	(0.272)	(0.191)	(0.220)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
B-QRFE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-0.489***	-0.569***	-0.252***	0.021	0.014
	(0.116)	(0.097)	(0.069)	(0.059)	(0.069)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
C- IV-QTE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-12.531***	-7.972***	-4.518***	-2.885***	-2.630***
	(2.507)	(1.708)	(0.971)	(0.579)	(0.517)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
D- QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	1.039	-0.592	0.457	-0.944***	-0.124*
	(0.839)	(0.931)	(0.687)	(0.161)	(0.066)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
E- IV QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	0.956	-3.742***	-3.278***	-2.859***	-0.274
	(0.671)	(1.440)	(0.387)	(0.481)	(0.354)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes

Note: Significance: *** 1%; ** 5%; * 10%. Standard errors are reported in the parenthesis. The combined sample contains 22,201 individuals (111,216 observations) from HILDA in 2009-2016. Panel A reports estimates using pooled QR from Koenker and Bassett, Jr. (1978); their standard errors are derived from 199 bootstraps. Panel B reports estimates using QRFE from Kato et al. (2012) method; their standard errors are derived from 199 sub-sampling technique (800 individuals over waves 9-16). Panel C reports estimates using IV-QTE from Abadie et al. (2002); their standard errors are derived from 199 bootstraps. Panels D and E report QRPD and IV QRPD from Powell (2016); their standard errors are clustered at individual level using the Markov Chain Carlo algorithm (MCMC) to solve the optimization problem. All regressions control for household income, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, regional and remoteness.

Table 4: Estimates of the Disaster Effect on Mental Health Score: Home owners

A-Pooled QR	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-2.074***	-1.747***	-1.137***	-0.485**	-0.384
	(0.693)	(0.456)	(0.287)	(0.223)	(0.252)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
B-QRFE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-0.426***	-0.471***	-0.16***	-0.021	-0.169***
	(0.115)	(0.084)	(0.061)	(0.051)	(0.063)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
C- IV-QTE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-9.069***	-5.332***	-3.007***	-2.127***	-1.863***
	(3.417)	(1.714)	(1.160)	(0.707)	(0.485)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
D- QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-1.589**	-3.358***	-2.517**	-1.312***	-0.064*
	(0.727)	(0.646)	(0.998)	(0.196)	(0.037)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
E- IV QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	1.437	-7.551***	-1.056***	-0.086	-0.453***
	(1.701)	(1.243)	(0.099)	(0.077)	(0.065)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes

Note: Significance: *** 1%; ** 5%; * 10%. Standard errors are reported in the parenthesis. The home owner sample contains 16,145 individuals (77,160 observations) from HILDA in 2009-2016. Panel A reports estimates using pooled QR from Koenker and Bassett, Jr. (1978); their standard errors are derived from 199 bootstraps. Panel B reports estimates using QRFE from Kato et al. (2012) method; their standard errors are derived from 199 sub-sampling technique (800 individuals over waves 9-16). Panel C reports estimates using IV-QTE from Abadie et al. (2002); their standard errors are derived from 199 bootstraps. Panels D and E report QRPD and IV QRPD from Powell (2016); their standard errors are clustered at individual level using the Markov Chain Carlo algorithm (MCMC) to solve the optimization problem. All regressions control for household income, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, regional and remoteness.

Table 5: Estimates of the Disaster Effect on Mental Health Score: Non-owners

A-Pooled QR	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-1.534	-1.765***	-0.756	-0.548	-0.693
	(1.105)	(0.549)	(0.489)	(0.342)	(0.526)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
B-QRFE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-0.341**	-0.183	0.083	0.368***	0.197*
	(0.147)	(0.124)	(0.105)	(0.096)	(0.105)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
C- IV-QTE	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-18.175***	-14.024***	-9.211***	-6.053***	-5.204***
	(4.928)	(3.300)	(2.668)	(1.822)	(1.818)
Individual Fes	No	No	No	No	No
State FEs	No	No	No	No	No
Year FEs	No	No	No	No	No
D- QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-2.615***	-0.985***	0.728**	0.229***	-0.738***
	(0.250)	(0.323)	(0.301)	(0.089)	(0.171)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
E- IV QRPD	**0.1 Quantile**	**.25 Quantile**	**.5 Quantile**	**.75 Quantile**	**.9 Quantile**
Damage	-2.845***	-5.118***	3.048***	0.033	-0.752***
	(0.876)	(0.823)	(1.057)	(0.291)	(0.116)
Individual Fes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes

Note: Significance: *** 1%; ** 5%; * 10%. Standard errors are reported in the parenthesis. The non-homeowner sample contains 9,547 individuals (31,052 observations) from HILDA in 2009-2016. Panel A reports estimates using pooled QR from Koenker and Bassett, Jr. (1978); their standard errors are derived from 199 bootstraps. Panel B reports estimates using QRFE from Kato et al. (2012) method; their standard errors are derived from 199 sub-sampling technique (800 individuals over waves 9-16). Panel C reports estimates using IV-QTE from Abadie et al. (2002); their standard errors are derived from 199 bootstraps. Panels D and E report QRPD and IV QRPD from Powell (2016); their standard errors are clustered at individual level using the Markov Chain Carlo algorithm (MCMC) to solve the optimization problem. All regressions control for household income, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, regional and remoteness.

Appendix

Table A1: First-Stage IV Diagnostics

	Full Sample	Home owners	Non-owners
disaster at state level	0.007***	0.005***	0.011***
	(0.001)	(0.001)	(0.002)
Individual FEs	yes	yes	yes
State FEs	yes	yes	yes
Year FEs	yes	yes	yes
Weak identification test			
Cragg-Donald statistic	37.81	15.44	19.33
Kleibergen-Paap statistic	38.32	15.68	20.08
Stock-Yogo critical values			
10% maximal IV relative bias	16.38	16.38	16.38
15% maximal IV relative bias	8.96	8.96	8.96
20% maximal IV relative bias	6.66	6.66	6.66
Observations	108,013	74,727	28,045
Individuals	18,998	13,712	6,540

Note: Dependent variable is '*Damage*'. Significance: *** 1%; ** 5%; * 10%. Standard errors are clustered at individual levels and reported in the parenthesis. All regressions control for household income, household size, age, age squared, marital status, tertiary education, occupation, health conditions, daily drinking and smoking, regional and remoteness.