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How Much Should We Pay for Mental Health Deterioration? The Subjective Monetary Value of Mental Health After the 27F Chilean Earthquake

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Abstract In this article we use the life satisfaction approach (LSA) to assess the non-pecuniary costs of Mental health impacts after the 2010 Chile earthquake. By linking both Subjective Well-Being valuation literature with studies that describe psychological impacts after natural disasters, we are able to quantify how big a compensation should be to leave individuals as well as they were before the event. Our results suggest that people who experience stress should be compensated by approximately 80% to 90% of the average monthly income if the shock was strong enough to cause significant damages. These estimates are robust to different empirical specifications, endogeneity, shock intensity measures, and mental health definitions. We estimate that the total costs of mental health deterioration are about 7% of the total reported damages, a significant amount that policymakers should not ignore in post-earthquake reconstruction stages.

Keywords Mental health · Subjective Well-Being · Life Satisfaction Approach · Economic Valuation · Natural Disasters · Monetary Compensation · PTSD

1 Introduction

On 27 February 2010, at 03:34 local time, a big[1] earthquake struck off the coast of central Chile, with intense shaking lasting for about three minutes. The earthquake (commonly referred as 27F or F-27 in the literature) killed at least 525 people, knocked down buildings, disrupted communications, and triggered a tsunami which devastated several coastal towns in south-central Chile. The 27F earthquake was the fifth largest event recorded by modern seismology at the time, and the economic costs were estimated at $30 USD billions.

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[1] 8.8 degrees in the Moment magnitude scale (MMS)

A natural disaster of such magnitude has not only economic repercussions in land and labor markets (Alexander, 1997; Naoi et al., 2007; Zhu et al., 2016; Jara and Faggian, 2018), but also important consequences for mental health in the short- and long-run, as empirical studies have shown that earthquakes affect negatively individuals' subjective well-being (Rehdanz et al., 2015; Ohtake and Yamada, 2013; Danzer and Danzer, 2016) and mental health (Wu et al., 2016; Shinfuku, 1996; Ramirez and Peek-Asa, 2005; Baryshnikova and Pham, 2018; Freedy et al., 1993).[2] The psychological impacts of natural disasters are not only important per se, but also because deterioration of mental health decreases the performance of workers and leads to lower overall productivity (Yamamura, 2012).

An important research agenda is the quantification of pecuniary and non-pecuniary costs after a disaster (Kessler, 2000; Kalia, 2002). Although the pecuniary damages and costs can be estimated, non-pecuniary damages (such as pain, suffering, psychological harm, loss of quality of life, or any other damages incurred that are foreseeable consequences of a disaster) are more difficult to compute due to the subjective nature of such costs (Sav, 1974), and because they have been mostly ignored in economic and risk analyses (Danzer and Danzer, 2016). Understanding how victims of a catastrophic event should be compensated is a constant issue for governments, societies, and organizations alike, and it is one of the most pressing issues that individual households have to face (Sayer et al., 2004; Akashah and Marks, 2006). In the specific case of the 27F disaster, there is a vast literature that shows the negative effects it has caused on the mental health of the population and across space (Cova and Rincon, 2010; Abeldaño et al., 2013; Andrades et al., 2018; Figueroa et al., 2010; García et al., 2014). However, to our knowledge, no attempt has been made in the literature to account for non-pecuniary costs of the earthquake due to mental health deterioration.

This paper attempts to fill that void by providing evidence on the monetary valuation of such mental costs, assessing the amount of income that an average individual needs to compensate and bear the negative effects of earthquake and tsunami on mental health. Specifically, the questions we try to answer are: (1) Is there an effect of the exposure to such disruptive event on individuals' mental health? (2) What is the equivalent monetary value of the disaster's mental health impacts? (3) Does the monetary valuation depends on how we measure the intensity of the earthquake/tsunami or mental health?

To achieve our goals, we use microdata taken before and after the earthquake, which allows us to control for several conditions before the event. Furthermore, we consider several macroseismic measures of earthquake's and tsunami's intensity using the USGS Shakemaps which are then imputed to each household using Geographical Information Systems. Most of the quantitative earthquake measures that we use in our models are generated using

[2] Similar evidence has been found for other environmental disasters such as floods (Luechinger and Raschky, 2009; Sekulova et al., 2016), droughts (Carroll et al., 2009), extreme weather events (von Möllendorff and Hirschfeld, 2016), and hurricanes (Berlemann, 2016).

methods that combine both instrumental intensities with local geology to produce maps of ground acceleration, amplitude and velocity (Wald et al., 2005), which are used to quantify earthquake intensity in broader terms at the local level (Wald et al., 1999; Worden et al., 2012). This allows us not only to check the robustness of our results, but also to analyze whether individuals are more perceptive to the ground's shake, the earthquake's velocity or to more subjective measures. To assess the monetary evaluation we rely on the Life Satisfaction Approach (LSA), which has been widely used to compute the price of attributes that do not have a market price (Clark and Oswald, 2002), and the subjective costs of natural disasters (Rehdanz et al., 2015; Luechinger and Raschky, 2009; Carroll et al., 2009; von Möllendorff and Hirschfeld, 2016).

In our opinion, this work makes several contributions. First, we use both true and perceived shaking of the ground based on the speed of acceleration of the ground. Previous studies have used the distance from the epicenter as the exposure to the earthquake (Peek-Asa et al., 2003, 2000), the number of reported dead or injured persons, destroyed or damaged buildings (Rehdanz et al., 2015), and also the new reports on the media (Ohtake and Yamada, 2013). However, as explained by Ramirez and Peek-Asa (2005), distance from the epicenter may misrepresent localized strength of shaking, because other factors, such as ground composition, landslide susceptibility and liquefaction, may affect the wave transmission during a seismic event. Thus, the measures used in this work provide more precise estimates of the true exposure to the earthquake not influenced by the built environment or the perception of motion. Second, we also provide more evidence about the non-pecuniary (short-run) costs of a destructive disaster in a middle-income country such as Chile, which is also located in one the one of the most highly seismic regions in the world (alongside Japan, Indonesia, and other countries in the pacific rim) (Lomnitz, 2004). Finally, we also use an instrumental variable (IV) approach to consider the potential endogeneity of our income measure.

The rest of this article is organized as follows: In Section 2 we start by reviewing studies that analyze the relationship between exposure to earthquakes/tsunami and mental health. In Section 3 we present the methodology to estimate income compensations. Section 4 presents the different measures of mental health, earthquake/tsunami intensities and the different controls used in this study. Our results and discussion section (Section 5) will be focused on determining at which impact level should policymakers start compensating individuals, as well as several robustness checks to sustain our conclusions. The final Section 6 concludes and discusses policy implications. Our bottom-line conclusion is that mental health impacts are significant (7% of the estimated total damages, approximately), and could be easily overlooked by policymakers in the post-earthquake reconstruction stages. This welfare loss due to deterioration of mental health is substantial and can be interpreted as an externality of the 27F disaster.

2 Literature review

The intensity and potential impacts of natural disasters have been increasing in past decades, leading to new challenges for social scientists and policy-makers (Alexander, 1997). In addition to the direct economic impacts of natural disasters (mostly disruptions and infrastructure damage) experiencing any significant disaster or extreme environmental event also affects negatively the individuals' well-being (Rehdanz et al., 2015; Luechinger, 2009; Ohtake and Yamada, 2013; Danzer and Danzer, 2016; Carroll et al., 2009), and has important short- and long-run repercussions on mental health (Baryshnikova and Pham, 2018) or psychopathological outcomes such as depression, trauma, post-traumatic stress disorder and anxiety disorders (Freedy et al., 1993; Galea et al., 2005). From a theoretical point of view, the link between mental health and the exposure to a natural disaster can be explained by the immediate traumatic exposure to life-threatening conditions (Ramirez and Peek-Asa, 2005), and the consequential negative life events (such as death of family or friends and loss of employment/housing) after the disaster (Galea et al., 2005).

Earthquakes, in particular, have attracted a lot of attention from researchers in different fields trying to understand behavioral changes in response to the impacts on stress and well-being they cause. The literature has shown that the health consequences of being exposed to an earthquake are not only related to mental health, such as the increased risks for major depression, anxiety disorders (Freedy et al., 1993; Shinfuku, 2011, 1996) and post-traumatic stress disorder (PTSD) (Ali et al., 2012; Wu et al., 2016), but also to other health-behavioral patterns including infection, nutrition and illness as an indirect effect (Phifer et al., 1988). The results from empirical works that analyze the exposure to earthquakes/tsunami and subjective well-being is mixed. For example Rehdanz et al. (2015) find that people living in a place affected by the Japan's 2011 great east tsunami experienced a drop in life happiness after the disaster, however no effect on people's happiness with the entire life is found. Using data collected 2-7 weeks after the same earthquake, Ohtake and Yamada (2013) find that negative relationship between the exposure to earthquake news and happiness. Similarly, Ishino et al. (2012) find that individuals that were badly hit by the earthquake and tsunami felt happier after the disaster than they did before. This result is corroborated by Yamamura (2012) who analyzes the long-term effect of the Hanshin-Awaji earthquake that occurred in Japan (1995) finding that the survivors to the disaster were significantly happier than the respondents from other not affected regions.

Mental health impacts of the 2010 Chile earthquake have also been described by public health and psychology literature (Zubizarreta et al., 2013). Abeldaño et al. (2013) point out that some regions and provinces close to the epicenter had higher prevalence of PTSD compared to the rest of the country, but the rates were still comparable to other disasters such as the 2007 earthquake in Pisco (Peru). Other studies have described the prevalence and persistence of post-traumatic growth and stress in children (Andrades et al., 2016, 2018) and women (Vitriol et al., 2013), while García et al. (2014) link post-

traumatic growth to religious coping and social support, finding that positive religious reappraisal helps to overcome trauma. In regards to the quantitative measure of PTSD we will be using in this study, it is worth noting that a validation study Leiva-Bianchi and Araneda (2013) was made for the Chilean context in this specific event.

In general, studies that offer monetary evaluations of the non-pecuniary costs of natural disasters have used the Life Satisfaction Approach (LSA) as preliminary tool.[3] For example, Danzer and Danzer (2016) use the LSA to estimate that the welfare losses due to the Chernobyl were around 2-6% of Ukraine's GDP 20 years after the disaster. Luechinger and Raschky (2009) estimate that individuals are willing to pay around 23.7% of their annual household income for the prevention of a flood disaster, and of around 0.7% for reducing the probability of flood from 2.6% to 0%, whereas Sekulova et al. (2016) find that the monetary value for experiencing a flood is about 94% of average income level and 96% for severe flood damages. The non-pecuniary costs of droughts has also been quantified by Carroll et al. (2009) in Australia. They find that doubling the frequency of spring droughts leads to the equivalent loss in life satisfaction of just over 1% of GDP annually. For earthquakes and tsunamis the literature is scarce. Rehdanz et al. (2015) found that the drop if life happiness in municipalities affected by the Japan 2011's tsunami is equivalent to 72% of annual income. Ohtake and Yamada (2013) estimate the monetary equivalent of approximately $25,600 USD (which represents the 70% of monthly income per capita) when front pages of newspapers were completely filled with negative news for the same disaster.

3 Methodology

3.1 Measuring income compensation

To compute the monetary valuation of the mental health costs due to the Chilean 27F-earthquake we use the economic concept of income compensation.[4] We consider that mental health for an individual i can be measured by a continuous but unobserved (latent) variable υ_i. We further assume that the maximum mental health output that an average individual can achieved in equilibrium is function of the following inputs:

$$\upsilon_i = h(r_i, y_i, \mathbf{x}_i, \epsilon_i), \tag{1}$$

where y stands for income, r is some measure of intensity or exposure to earthquake (or tsunami), and $\mathbf{x}$ stands for a vector of other variables that

[3] The Life Satisfaction Approach has also been used to value intangibles as diverse as airport noise Van Praag and Baarsma (2005) and terrorism Frey et al. (2009).

[4] For a further review of welfare measures in economics see Bockstael and Freeman (2005). Van Praag and Baarsma (2005), Welsch and Kühling (2009) and Frey et al. (2009) provide good examples of how these measures can be used under the LSA to compute the monetized value of intangible goods.

affect individuals' mental health (education, physical health, etc.). We add also the error term ϵ_i since we are not able to control for all possible factors that affect true mental health. We also assume that higher values of υ_i implies an improvement of mental health, such that $\partial \upsilon_i / \partial y_i > 0$ and $\partial \upsilon_i / \partial r_i < 0$, that is, more income increases mental health and the exposure to earthquake reduces it (Kessler, 2000; Galea et al., 2005).

We are particularly interested in the psychological non-pecuniary costs caused by the 2010 Chile earthquake and tsunami. To compute such costs, we ask ourselves: *how much additional income an average individual would require to offset the negative impact of the earthquake so she/he can be as well-off as before the shock?*[5]

LSA provides at least two different ways of computing such income compensation (Welsch and Kühling, 2009). One measure typically used is the marginal welfare change for a change in r, which can be derived by differentiating the indirect mental health Equation (1) and expressing the change in y necessary to compensate for the change in r, keeping mental health constant, yielding:

$$\overline{MV} = \frac{dy}{dr} = -\frac{\partial h_i / \partial r_i}{\partial h_i / \partial y_i}, \tag{2}$$

where $\overline{MV}$ represents the average marginal value. In the economic literature, this is also known as the marginal rate of substitution between mental health and income, and represents the amount of income necessary to compensate for a one-unit increase in earthquake intensity (Johansson, 1987).[6] It should be noted that under our formulation, the sign of (2) should be positive and represents the trade-off between income and earthquake intensity that will leave individuals, on average, as mentally healthy as they were before.

The concept of compensating variation (CV) is also used for *"non-marginal changes"* (Bockstael and Freeman, 2005). The CV for a discrete change in r is defined as:

$$h(y_{i0}; r_{i0}; \mathbf{x}_{i0}) = h(y_{i0} - CV; r_{i1}, \mathbf{x}_{i0}), \tag{3}$$

where the 0 and 1 denote initial (before the earthquake) and final (after the earthquake) levels of the parameters, respectively. Given an earthquake-intensity increase from r_{i0} to r_{i1}, equation (3) answers the question about the minimum income needed to get to the original level of mental health. This is also known in the economic valuation literature as willingness to accept (WTA), and it is an *expost* evaluation.

3.2 Econometric approach

To compute the welfare measures, we need to estimate Equation (1). However, we do not observe the true mental health of individuals υ_i, but rather some

[5] Another approach to compute the non-pecuniary costs of an earthquake would be to compute a Quality of Life Index using hedonic price models as in Naoi et al. (2007).

[6] Annex B presents the derivation of Equation (2).

continuous measure based on self-rating scale(s), h^*_{i1}, which we assume is a linear function of $(r_i, y_i, \mathbf{x}_i)$:

$$h^*_{i1} = \alpha + \beta \ln(y_{i0}) + \gamma r_i + \mathbf{x}'_{i0}\boldsymbol{\delta} + \epsilon_{i0}, \quad i = 1, ..., N, \tag{4}$$

where r_i is some measure of the intensity of the earthquake/tsunami that took place on February 27th, 2010; $\ln(y_{i0})$ is the natural logarithm of the monthly household income and $\mathbf{x}_{i0}$ is a set of controls measured before the earthquake (2009).[7]

In this study, we use three different dependent variables measured after the earthquake which are further explained in Section 4.2: a continuous measure based on a self-rating scale for post-traumatic stress disorder (PTSD) (Davidson Trauma Scale (DTS), see Davidson et al., 1987), a dummy variable indicating the prevalence of PTSD, and a variable for the individuals' perception of their health in general. Thus, given the nature of our proxies for mental health (continuous, dichotomous or categorical) we estimate Equation (4) by Ordinary Least Squares (OLS), Binary Probit and Ordered Probit models.

Using Model (4), Equation (2) can be computed as:

$$\overline{MV} = \frac{dy_i}{dr_i} = -\frac{\gamma}{\beta} y_i, \tag{5}$$

where y_i is the monthly household income for individual i. Similarly, solving for CV in Equation (3) can be computed as:[8]

$$CV = y_{i0}\left[1 - \exp\left(\frac{\gamma}{\beta}(r_{i1} - r_{i0})\right)\right]. \tag{6}$$

Empirical studies using the LSA have used these measures indistinctly. Equation (5) has been used by Clark and Oswald (2002) and Levinson (2012) for air pollution, Van Praag and Baarsma (2005) for noise pollution, and Powdthavee (2008) to estimate the monetary value of life satisfaction gained by an increase in the frequency of interaction with friends, relatives and neighbors. On the other hand, Equation (6) has been used by Luechinger (2009) to value air quality and Frey et al. (2009) for terrorism.

Regardless of the model used to estimate the parameters of Equation (4)—and therefore, compensatory variations—we need to assume that both $\ln(y_{i0})$ and r_i are exogenous variables. Exogeneity of r_i is partially assured since the earthquake is a completely random unforeseeable shock and therefore exogenous. Thus, it is somehow safe to assume that $\mathbb{E}(r_i \cdot \epsilon_{i0}) = 0$, $\forall i = 1, ..., N$.[9]

[7] Good controls are those likely to have an effect on mental health and income, but that are not themselves affected by mental health, income or the earthquake/tsunami intensity (Angrist and Pischke, 2008). Thus, we refrain to include any variables measured after the earthquake took place as controls.

[8] See Annex B.

[9] Even though the immediate shock was unexpected, the whole country is known for frequent earthquake activity that could have affected past firm and household decisions. Fortunately, since every region in Chile has had major earthquakes in the past, there is no credible possibility of self-sorting into "earthquake-free zones", therefore we have a strong case to claim exogeneity at least for our earthquake/tsunami measures.

However, the exogeneity of y_{i0} is more difficult to argue (Ettner, 1996). Income may be affected by factors that also have a direct effect on mental health. If such factors are not observed (or not controlled for), then the estimated coefficients might be biased. As an example, an individual with a genetic predisposition towards mental illness may be less productive and hence earn less reducing household income. Another potential omitted variable highly correlated with income (and health) is social background. Furthermore, the theoretical and applied literature have shown that individuals with good both psychical and mental health have in average higher labor force participation rates and higher wages, both of which lead to higher household income and implying a potential reverse causality (Ettner, 1996; Lindahl, 2005; Bilger and Carrieri, 2013). In particular, poor mental health may restrict a household's capacity to earn income or to accumulate assets by limiting work or by raising medical expenses. Given the potential endogeneity of household income, we estimate an IV procedure to reduce the potential biases of $\widehat{\beta}$, where the first step is given by the following reduced equation:

$$\ln(y_{i0}) = \lambda z_{i0} + \mathbf{x}_{i0}'\boldsymbol{\gamma} + \upsilon_{i0}, \tag{7}$$

where z_{i0} is an instrument, and $\mathbf{x}_{i0}$ is the set of assumed pre-determined variables in Equation (4). Following Bilger and Carrieri (2013) and Ettner (1996), we use as instrument a dummy variable indicating whether the household receive non-earnings income in 2009 for $\ln(y_{i0})$. The exclusion restriction, $\text{Cov}(z_{i0}, \epsilon_{i0}) = 0$, can be argued considering that income that does not come from work activities that require being in good health (Ettner, 1996; Bilger and Carrieri, 2013), therefore this variable only impact health through its effect on family income. Finally, Bilger and Carrieri (2013, pag. 3) note that the endogeneity of income explaining individual health should remain fairly limited if income is measured at the household level. We maintain the same argument here.

4 Data

4.1 Survey and sample

For this paper we rely on household survey data collected by the Chilean Ministry of Social Development before and after the earthquake. The initial wave was originally intended as a cross sectional dataset (CASEN 2009), but due to the extensive nature of the Earthquake that struck central Chile in February 2010, a follow-up survey was conducted, and expanded the sample to build a panel survey in the affected areas (CASEN-PT 2010, or Post-Earthquake Survey (PES)).[10] The first round of data was collected 3 months before the earthquake (November 2009), and then repeated 3 months after it

[10] The sample can be downloaded at `http://observatorio.ministeriodesarrollosocial.gob.cl/enc_post.php`.

(May-June). The survey is regionally representative for the 6 administrative regions covering 80% of the country's population, and includes detailed questions about income, human capital, and other socio-economic variables that describe households and individuals.[11]

Given how potentially disruptive an 8.8 earthquake could be, follow-up efforts were high, and the attrition rate was relatively small (2.5%). Furthermore, the survey was over-sampled at the second period in time (2010), and we did not observe significant internal or external migration movements during those months, at least in this sample. In any case, we do not consider those individuals who were living in a different commune at the time of the earthquake in our estimates.[12] The final sample, after cleaning for missing values in the covariates, is composed of 20,055 individuals.[13]

4.2 Dependent variables and controls

We use three different dependent variables for h^*_{1i}—after the earthquake—in Equation (4). The first two variables are related to the psychological shock that could potentially have caused the earthquake and subsequent tsunami based on the Davidson Trauma Scale (DTS) to measure Post Traumatic Stress Disorder (Davidson et al., 1987, 1997), which asks individuals about the intensity, and frequency of the symptoms associated to PTSD. This scale has been tested and validated in different sets of populations (Davidson et al., 2002; Ali et al., 2012) and particularly in Chile (Leiva-Bianchi and Araneda, 2013). In our sample, the 34 questions were answered by at least one person per household.[14] We use the continuous version (or DTS) of such scale and a measure of prevalence of PTSD, which takes the value of 1 if DTS is greater or equal to some threshold. The third variable used as proxy of individual health-status is self-assessed health (SAH) status, which is obtained from the answer to the question *"In general, how would you rate hour health?"* The range of responses corresponds to a likert scale ranging from 1 "Poor" to 7 "Excellent". This measure has also been used in other studies analyzing the relationship between mental health and natural disasters (Phifer et al., 1988; Baryshnikova and Pham, 2018) and its relationship with subjective well-being measures as a whole (Böckerman et al., 2011). Furthermore, the World Health Organization (WHO) states that

[11] The regions affected by 27-F earthquake are Valparaiso, Metropolitana, Libertador Bernando O'Higgins, Maule, Biobio and Araucania. See Figure 1.

[12] They correspond to the 6.1% of the raw sample.

[13] One of the reviewers raised the concern of the potential relationship between the attrition and the negative experiences related to the 2010 earthquake. We regress the non-response dummy variable on some earthquake intensities controlling for several factors using a Probit Model. The results, available upon request, show no significant association between the non-response and the exposure to the earthquake.

[14] Although the total sample of the CASEN-PT survey corresponds to 62,194 individuals, only the individuals present in the interview (21,603) answered the questions related to PTSD.

this variable is able to capture not only physical health, but also mental and social well-being.

Table 1 presents summary statistics for the sample used in the main regressions. The average of the DTS scale is about 18.75 with considerable dispersion ($sd = 33.80$). The general prevalence is about 15%, which is greater than the prevalence of 4.4% reported after 3 years of the Taiwan's earthquake, but lower than the prevalence observed in the Peruvian earthquake in 2007 (25.2%) (see Abeldaño et al., 2013, and citations therein). The distribution of SAH is mostly skewed to the right with an average of ≈5 points, revealing that self-perception of health post-earthquake is generally good if we consider health as a whole.

We use several characteristics of individuals and cities (before the earthquake) as controls that are common in the PTSD literature (see for example Ali et al., 2012; Andrades et al., 2018). The variables at the individual level are age, schooling, gender, whether the individual is the household head, previous health condition, labor and marital status. Table 1 shows that the average of age in the sample is approximately 50 years, whereas men account for almost 31% of to total sample. Almost half of the sample is out of the labor force (OLS) and 64% is married or cohabiting. The individuals with health problems in 2009 represent the 19%.[15] We also include dummy variables indicating the housing quality (HQ) before the earthquake: 70% of the sample was living in a dwelling considered of good quality before the earthquake. The variables at the city level are density and whether the city is located in the coast. Household monthly income includes wages from the main job for each household member (contract work, self-employment, etc.). To convert household income from Chilean pesos to US dollars we use the average exchange rate for 2009 (which did not fluctuate widely during those months).

4.3 Shock measures

To approximate the impact of the earthquake on mental health, we need quantifiable measures of the earthquake's strength over space. Furthermore, since the mental health of individuals after such a severe event will depend on the intensity and magnitude of the earthquake, as well as the building construction and their propensity to collapse (Ramirez and Peek-Asa, 2005), we need measures that quantify the exposure of individuals to such factors.

In this study three different macroseismic intensity measurements are considered using the USGS Shakemaps as a source (Wald et al., 2005): Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), and the Modified Mercalli Intensity (MMI). These shock measurements are correlated with each other (see Figure A.1), yet they have differences worth considering for the interpretation and description of the earthquake impacts. PGA is the highest acceleration in an area, and is measured in rates of gravity acceleration

[15] The question was: "In the last 30 days have you have a health problem?"

Table 1 Summary Statistics

	Mean	SD	Min	Max	N
Davidson Trauma Scale (DTS)	18.75	33.80	0.00	256.00	20055
Prevalence	0.15	0.36	0.00	1.00	20055
SAH	4.98	1.38	1.00	7.00	19995
Eartquake intensity:					
PGA (Peak ground acceleration in % g)	0.25	0.04	0.11	0.35	20055
MMI (Modified Mercalli scale)	7.03	0.42	5.50	7.81	20055
PGV (Peack ground velocity in cm/s)	23.34	5.48	7.43	37.72	20055
Tsunami's wave:					
Not exposed to tsunami	0.75	0.44	0.00	1.00	20055
Exposed to waves lower than 3 meters	0.14	0.35	0.00	1.00	20055
Exposed to waves higher than 3 meters	0.11	0.31	0.00	1.00	20055
Instrument:					
Household receive rent from properties and land?	0.04	0.20	0.00	1.00	20055
Controls before earthquake:					
Household Income (USD)	910.75	859.23	4.18	18194.92	20055
Log(Household Income (USD))	6.54	0.74	1.43	9.81	20055
Age	49.85	17.14	15.00	100.00	20055
Schooling	8.37	4.30	0.00	20.00	20055
Household size	3.68	1.74	1.00	14.00	20055
Male	0.31	0.46	0.00	1.00	20055
Household head	0.46	0.50	0.00	1.00	20055
Health problems	0.19	0.39	0.00	1.00	20055
Employed	0.41	0.49	0.00	1.00	20055
Unemployed	0.04	0.20	0.00	1.00	20055
OLF	0.55	0.50	0.00	1.00	20055
Married	0.64	0.48	0.00	1.00	20055
Divorced	0.07	0.25	0.00	1.00	20055
Widowed	0.10	0.30	0.00	1.00	20055
Single	0.19	0.39	0.00	1.00	20055
Acceptable HQ	0.70	0.46	0.00	1.00	20055
Recoverable HQ	0.28	0.45	0.00	1.00	20055
Unrecoverable HQ	0.02	0.14	0.00	1.00	20055
Density	0.02	0.03	0.00	0.16	20055
Coast city	0.25	0.44	0.00	1.00	20055

Note: Sample use in regressions. See Section 4 for an explanation of the variables.

units ($g = 9.8^{m}/_{s^2}$, so $0.5PGA$ is equivalent to $4.9^{m}/_{s^2}$), while PGV captures maximum velocity ($^{cm}/_{s}$). The MMI measure combines both acceleration and velocity with observed (subjective) intensity to generate an estimate of potential damage, which is assigned to a numeric scale (Wald et al., 1999). Although both PGA and PGV provide a measure of instrumental intensity, that is, ground shaking recorded by seismic instrument, according to Wald et al. (2005) people are more sensitive to ground acceleration than velocity, whereas structures are more susceptible to velocity than acceleration.[16] MMI quantifies the effects on the Earth's surface, humans, man-made structures, etc, and it

[16] PGA is often a good predictor of both fatal and nonfatal injuries (Peek-Asa et al., 2003; Mahue-Giangreco et al., 2001)

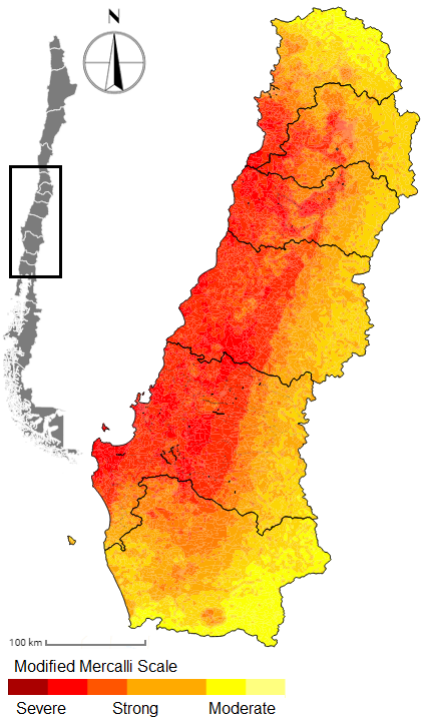

Fig. 1 Modified Mercalli Intensity (MMI) across Chilean regions affected by the 2010 Earthquake. Source: USGS shakemaps.

is intended to capture how the earthquake was felt by people, and hence, it is a subjective scale of earthquake intensity.

All three geological shock variables are calculated at the smallest statistical sampling unit obtainable, and assigned accordingly to each household in the affected area.[17] As an illustration, Figure 1 plots the spatial distribution of earthquake's intensity using the MMI scale for the Chilean regions that were affected.

The measurement units are important both to determine cutoff levels and to interpret our coefficients, showing us implicitly how much compensation per additional unit of acceleration $(\$/\%g)$, velocity $(\$\cdot s/cm)$, or intensity degrees $(\$/MMIunit)$ an individual should be entitled to. To illustrate the differences between them, Table 2 shows the differences between measurement units and how strong people perceive shaking and the potential damage.

As an illustration, the maximum MMI in our dataset is 7.81 (see Table 1), so according to Table 2 people located in regions with such intensity perceived a very strong shaking and moderate damage. However, considering the max-

[17] The affected area corresponds to 150 municipalities, which range from entirely rural areas to big cities containing both urban and rural areas.

imum PGA and PGV, individuals who suffered the highest intensity of the earthquake perceived a severe shaking and moderate to heavy damage.

Finally, a wave-height measurement is also included for the coastal areas that were hit by the Tsunami. Table 1 shows that 25% of the sample was affected by the tsunami and 11% was exposed to waves higher than 3 meters.

Table 2 Ranges of intensity of peak ground acceleration (PGA), velocity (PGV), and Modified Mercalli Intensities (MMI)

Perceived Shaking	Potential Damage	PGA (%g)	PGV (cm/s)	MMI
Not felt	None	<0.0017	<0.1	I
Weak	None	0.0017 — 0.014	0.1 —- 1.1	II—III
Light	None	0.014 — 0.039	1.1 — 3.4	IV
Moderate	Very light	0.039 —- 0.092	3.4 — 8.1	V
Strong	Light	0.092 — 0.18	8.1 —- 16	VI
Very strong	Moderate	0.18 — 0.34	16 — 31	VII
Severe	Moderate to heavy	0.34 — 0.65	31 — 60	VIII
Violent	Heavy	0.65 — 1.24	60 —- 116	IX
Extreme	Very heavy	>1.24	>116	X+

Source: USGS Shakemaps, calculated using data from Worden et al. (2012).

5 Results

5.1 Sensitivity to earthquake and tsunami intensity measures

The first question we try to answer is whether the relationship between mental health and earthquake/tsunami intensity depends on how we measure its strength over space and/or the functional form.

Table 3 presents the OLS results for the relationship between our measures of earthquake intensity (r_i) and the "inverse of DTS" as a continuous variable in model 4.[18] For each r_i measure, we estimate both a linear and quadratic specification controlling for several variables before the earthquake.[19] By including the quadratic term of earthquake intensity we formally test whether higher intensity implies higher impact on mental health.[20]

As expected, all specifications where r_i enters linearly show a significant negative relationship. However, the quadratic specification works well just for PGA and MMI intensities. To shed some light in the adequacy of the quadratic term, Figure 2 shows the marginal impact of our 3 measures for the specifications 2, 4 and 6 from Table 3. From panel A, we observe that the negative

[18] We choose to use the inverse of the DTS to maintain the same interpretation as in our theoretical model presented in Section 3.

[19] To take into account of a potential correlation of residuals when individuals are taken from the same city, cluster standard errors at the city level are used in all specifications.

[20] We also test whether income has a diminishing marginal effect on mental health. Table A.1 in Appendix show that, at least for this sample, the relationship between income and mental health is linear.

Table 3 Sensitivity analysis for earthquake-intensity measures (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
PGA	-121.791***	276.943*				
	(16.950)	(150.164)				
PGA^2		-827.594**				
		(320.261)				
MMI			-12.549***	91.197**		
			(1.737)	(44.495)		
MMI^2				-7.502**		
				(3.261)		
PGV					-0.970***	-0.256
					(0.134)	(0.984)
PGV^2						-0.016
						(0.022)
Log of Household Income (USD)	2.285***	2.204***	2.235***	2.164***	2.177***	2.164***
	(0.511)	(0.509)	(0.507)	(0.506)	(0.505)	(0.504)
Male	9.033***	9.083***	9.020***	9.079***	9.022***	9.029***
	(0.765)	(0.757)	(0.759)	(0.752)	(0.758)	(0.756)
Age	-0.380***	-0.376***	-0.380***	-0.375***	-0.376***	-0.376***
	(0.100)	(0.101)	(0.100)	(0.100)	(0.100)	(0.100)
Age^2	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household Head	-0.593	-0.540	-0.591	-0.567	-0.597	-0.589
	(0.687)	(0.686)	(0.687)	(0.688)	(0.689)	(0.691)
Schooling	0.361***	0.373***	0.354***	0.363***	0.364***	0.371***
	(0.089)	(0.089)	(0.088)	(0.088)	(0.088)	(0.089)
Health Problems	-6.614***	-6.581***	-6.668***	-6.631***	-6.587***	-6.546***
	(0.918)	(0.904)	(0.921)	(0.912)	(0.911)	(0.908)
Household size	-0.296	-0.285	-0.305	-0.301	-0.297	-0.296
	(0.204)	(0.202)	(0.204)	(0.203)	(0.205)	(0.205)
Employed as reference						
- *Unemployed*	-2.295	-2.211	-2.283	-2.255	-2.283	-2.266
	(1.460)	(1.452)	(1.457)	(1.455)	(1.456)	(1.455)
- *OLF*	-0.086	0.021	-0.079	-0.015	-0.063	-0.046
	(0.637)	(0.629)	(0.639)	(0.634)	(0.637)	(0.638)
Married as reference						
- *Divorced*	0.289	0.256	0.182	0.107	0.127	0.117
	(1.041)	(1.047)	(1.039)	(1.043)	(1.038)	(1.039)
- *Widowed*	-0.004	-0.064	-0.047	-0.106	-0.047	-0.065
	(1.059)	(1.047)	(1.055)	(1.045)	(1.051)	(1.048)
- *Single*	1.831**	1.856**	1.807**	1.842**	1.865**	1.889**
	(0.761)	(0.759)	(0.760)	(0.758)	(0.763)	(0.759)
Acceptable HQ as reference						
- *Recoverable HQ*	-0.526	-0.645	-0.527	-0.597	-0.585	-0.618
	(0.869)	(0.856)	(0.870)	(0.859)	(0.864)	(0.861)
- *Unrecoverable HQ*	-1.980	-2.569	-2.068	-2.570	-2.262	-2.443
	(2.413)	(2.388)	(2.417)	(2.399)	(2.401)	(2.398)
Coast	-2.416	-1.104	-3.061	-2.341	-3.318*	-3.178
	(1.994)	(1.930)	(1.978)	(1.945)	(1.966)	(1.974)
Density	38.561*	28.161	45.577**	35.227	44.827**	41.967*
	(22.461)	(22.820)	(22.720)	(23.224)	(21.769)	(22.523)
Constant	2.692	-43.646**	60.622***	-296.449*	-4.725	-12.425
	(5.651)	(17.321)	(12.280)	(151.433)	(4.807)	(11.056)
Observations	20055	20055	20055	20055	20055	20055
R^2 Adjusted	0.061	0.064	0.062	0.064	0.063	0.064
Turning point for earthquake		0.167		6.079		-8.228
Turning point for age	53.054	52.982	53.145	53.115	53.039	53.003

Notes: Standard errors clustered at the city level in parenthesis.
Turning point for earthquake and age are computed as $-\widehat{\beta}_x/(2 \times \widehat{\beta}_{x^2})$, where $\widehat{\beta}_x$ and $\widehat{\beta}_{x^2}$ are the estimate for the linear and quadratic term, respectively.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

impact of PGA occurs when it is equal to 0.167%g (see also the bottom of Table 3), however it becomes significant when PGA is $\geq$ 0.2%g units. That is, PGA correlates negatively with mental health when perceived shaking is very strong, and potential damage is moderate (see Table 2). It is important to recall that PGA is not a measure of the total energy of an earthquake, but rather of how hard the earth shakes at a given spatial location. Similarly, the marginal impact of MMI becomes negative when MMI is approximately 6. That is, when the perceived shaking is strong and the potential damage is light. However, below 6.5 the effect is not different from zero at 95% confidence interval. For the remaining measure (PGV), it seems that the marginal impact is negative across all possible values, but slightly increasing. Yet, the point estimates are estimated with more precision for the averages. We postulate two reasons for the lack of adjustment of the quadratic term. First, it might be due to the small fraction of individuals exposed to low earthquake intensities. For example, the histogram in Figure 3 shows that there are few cities with PGA lower than 0.167, which could be affecting the precision of the estimates below this intensity. Second, it might be the case that our measures already include the increasing intensity by construction (Wald et al., 2005).

The results for the controls are as expected and very stable in terms of sign and significance across all specifications.[21] For example, individuals tend to report higher levels for mental health as household income increases. The estimated coefficients show that an increase of 1% in household income is correlated with an increase of approximately 0.02 points in mental health, holding everything else constant. The coefficient for *Male* is positive and highly significant implying that men have approximately 9 points lower of DTS after the earthquake than women. Age has the typical U-shape: mental health decreases with age until it reaches a critical minimum. The turning point (or minimum mental health) is achieved after age 53. We also found that being head of the family, unemployed or out of the labor force before the earthquake are not correlated with the our continuous DTS measure.[22] As expected, years of schooling are positively correlated with mental health after the earthquake, and the coefficient is highly significant. Presence of health problems increases DTS in about 6.5 points more than healthy individuals. However, we do not find systematic differences between being married or cohabiting, and being widowed or divorced. Just being single shows a significant negative difference: single individuals seem to have better mental health than married ones.[23] Finally, the remaining two variables at the city level included are *Coast* and *Density*. Although their signs are stable across all the specifications, their significance depends on the measures of intensity used.

[21] An important control is whether the individuals are religious-minded and have social capital (Ali et al., 2012). However, our survey data does not provide detailed information about these dimensions.

[22] This contrasts with the results for the earthquake in Pakistan found by Ali et al. (2012), which show that being the head of the family is one of the strongest predictors of PTSD.

[23] Note that this contradicts the hypothesis that individuals with better social networks are more resilient.

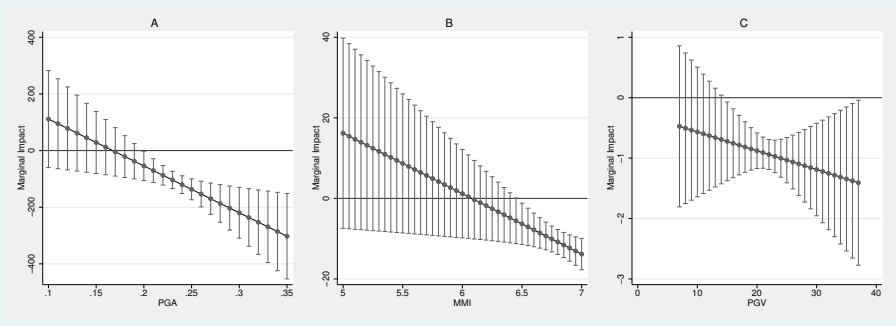

Fig. 2 Marginal effect of earthquake intensity on the inverse of DTS for models with a quadratic term. 95% confidence interval. Panel A, B and C shows $\partial h/\partial r_i$ for models 2, 4 and 6 from Table 3, respectively. Standard errors computed using Delta Method and clustered standard errors at the city level. Source: Own elaboration.

Next, we analyze the relationship between being affected by the tsunami and the inverse of DTS. Table 4 shows two specifications where the same controls as in Table 3 were used. The model of column 1 includes a dummy variable indicating whether the individual was living in a city affected by the tsunami (waves were greater than 0.9 meters), whereas model 2 includes a categorical variable indicating the height of the wave in each city. The results show that, in average, individuals exposed to the tsunami have approximately 5.4 more DTS points than those who were not exposed. However, model 2 shows that individuals exposed to waves more than 3 meters of height were the most affected, being in average 15 DTS points higher than those that were not exposed to them.

In summary, all earthquake intensity measurements are highly correlated with DTS: the higher the earthquake exposure, the lower the individuals' mental health after 5 months of the earthquake. However, specifications with the quadratic term show that the association is negative and significant only when the perceived shaking is moderate/strong and the potential damage is very light/light. In addition, it is important to understand the differences in the magnitudes of the coefficients for each of the measurements. For example, considering only the models without the quadratic term, it can be seen that the estimated coefficient for PGA is approximately 122. That is, an increase in 1 g unit in PGA is correlated with an increase of 122 DTS points, which is much larger than the coefficients of the other two measures. This result can be understood if one considers that an increase from 0 to 1 in PGA is similar to a perception of movement from *"not felt"* to *"violent"*. In other words, an increase from 0 to 1 in PGA is similar to an increase from I to IX in the Mercalli scale. Note that multiplying the MMI's coefficient (model 3) by 10 gives us roughly the same coefficient as PGA.

Table 4 Sensitivity analysis to tsunami measures (OLS)

	(1)	(2)
Affected by tsunami	-5.400**	
	(2.404)	
No wave as reference		
0m < Wave < 3m		1.628
		(2.157)
Wave > 3m		-14.739***
		(3.206)
log of Household Income (USD)	2.577***	2.315***
	(0.529)	(0.527)
Male	9.021***	9.104***
	(0.750)	(0.763)
Age	-0.403***	-0.397***
	(0.101)	(0.100)
Age^2	0.004***	0.004***
	(0.001)	(0.001)
Household Head	-0.600	-0.688
	(0.691)	(0.684)
Schooling	0.384***	0.344***
	(0.095)	(0.096)
Health Problems	-6.607***	-6.720***
	(0.988)	(0.955)
Household size	-0.359*	-0.319
	(0.206)	(0.204)
Employed as reference		
- *Unemployed*	-2.040	-2.216
	(1.484)	(1.486)
- *OLF*	-0.156	-0.079
	(0.639)	(0.642)
Married as reference		
- *Divorced*	0.629	0.172
	(1.053)	(1.092)
- *Widowed*	-0.151	-0.247
	(1.093)	(1.078)
- *Single*	1.953**	1.903**
	(0.772)	(0.771)
Acceptable HQ as reference		
- *Recoverable HQ*	0.098	-0.075
	(0.845)	(0.856)
- *Unrecoverable HQ*	-1.926	-1.205
	(2.437)	(2.605)
Density	34.281	36.817
	(25.758)	(23.558)
Constant	-28.891***	-26.968***
	(4.484)	(4.573)
Observations	20055	20055
R^2 Adjusted	0.040	0.054

Notes: Standard errors clustered at the city level in parenthesis.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

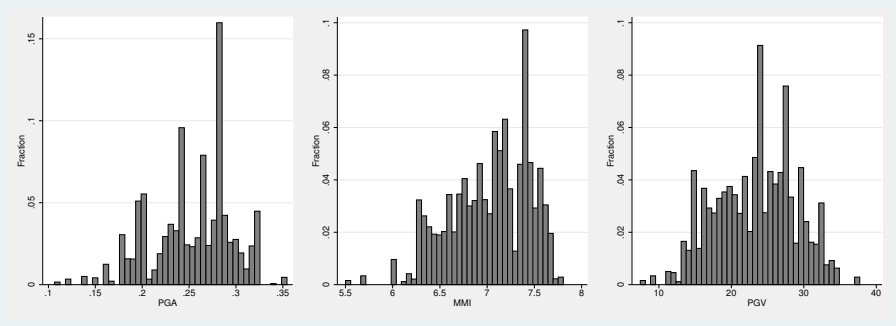

Fig. 3 Distribution of earthquake-intensity measures. PGA is peak ground acceleration; MMI is the modified Mercalli scale, and PGV is the peak ground velocity. Source: Own elaboration based on USGS shakemaps.

5.2 Sensitivity to mental health variable

In this section, we test whether the previous relationship holds if we change our dependent variable. Specifically, we run two additional models using as dependent variable the no-prevalence of post-traumatic stress disorder and self-assesses health status (SAH). No-prevalence was treated as a dichotomous variable in which a score of 40 or lower was assumed in the Davidson Trauma Scale as the absence of post-traumatic stress disorders (Davidson et al., 1997; Leiva-Bianchi and Araneda, 2013; Ali et al., 2012).

The partial changes for a Probit model using the no-prevalence indicator as dependent variable are shown in Table 5.[24] We use the same controls as in previous regressions. However, we did not include the quadratic term since it was not significant for any of the intensity variables. The models deliver qualitatively the same results as in Table 3 and 4. For example, an increase of one point in PGA decreases the probability of no-prevalence by 1.3 in a 0 to 1 scale, whereas an increase of one point in the MMI scale decreases it by 13 percentage points. Similarly, if the individuals were exposed to the tsunami, then they would be a 6.2% more likely to have post-traumatic stress disorder than those who were not. While those who experienced waves of more than three meters are 16% more likely to have PTSD than those who were not exposed to the tsunami.

Table 6 presents the partial change for an ordered Probit (OPM) model on the probability of reporting an excellent subjective health status (SAH = 7). An increase in any of our three measures of earthquake intensity reduces the probability of $\Pr(SAH = 7)$ by 8.4%, 1.1% and 0.1% respectively. However, we do not find evidence that being affected by the tsunami has a detrimental effect on the subjective perception of health.

[24] Standard errors were clustered at the city level in the Probit Model. Partial effects were computed at the mean of the variables, whereas standard errors were computed using Delta method. The marginal impact for dummy variables is the discrete change from the reference level.

Table 5 Sensitivity analysis for no-prevalence (Marginal effects from Probit Model)

	(1) ME / SE	(2) ME / SE	(3) ME / SE	(4) ME / SE	(5) ME / SE
PGA	-1.255***				
	(0.181)				
MMI		-0.129***			
		(0.018)			
PGV			-0.010***		
			(0.001)		
Affected by tsunami				-0.062***	
				(0.025)	
No wave as reference					
0m < Wave < 3m					0.010
					(0.022)
Wave > 3m					-0.157***
					(0.033)
log of Household Income (USD)	0.025***	0.024***	0.024***	0.028***	0.026***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Male	0.087***	0.086***	0.087***	0.087***	0.088***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Head	-0.013	-0.012	-0.013*	-0.013	-0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Schooling	0.003***	0.002***	0.003***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Health Problems	-0.055***	-0.056***	-0.055***	-0.056***	-0.057***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Household size	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Employed as reference					
- *Unemployed*	-0.035**	-0.035**	-0.035**	-0.033**	-0.035**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
- *OLF*	-0.004	-0.004	-0.004	-0.006	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Married as reference					
- *Divorced*	0.007	0.005	0.005	0.010	0.005
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
- *Widowed*	0.009	0.008	0.008	0.008	0.007
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
- *Single*	0.019**	0.019**	0.020**	0.021**	0.020**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Acceptable HQ as reference					
- *Recoverable HQ*	-0.005	-0.005	-0.006	0.001	-0.001
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
- *Unrecoverable HQ*	-0.022	-0.023	-0.025	-0.019	-0.014
	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
Coast	-0.025	-0.033*	-0.037**		
	(0.018)	(0.018)	(0.018)		
Density	0.346	0.398	0.412	0.329	0.361
	(0.274)	(0.275)	(0.267)	(0.318)	(0.290)
Observations	20055	20055	20055	20055	20055

Notes: Estimates correspond to the marginal change evaluated at the mean of the variables using a Probit Model.
SE clustered at the city level were used in the Probit Model, whereas the SE for the marginal changes in parenthesis were computed using Delta Method.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 6 Sensitivity analysis for SAH (Marginal effects from OPM on Pr(SAH = Excellent))

	(1) ME / SE	(2) ME / SE	(3) ME / SE	(4) ME / SE	(5) ME / SE
PGAW	-0.084**				
	(0.036)				
MIW		-0.011***			
		(0.004)			
PGVW			-0.001***		
			(0.000)		
Affected by tsunami				0.002	
				(0.004)	
No wave as reference					
0m < Wave < 3m					0.005
					(0.004)
Wave > 3m					-0.001
					(0.006)
Log of Household Income (USD)	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Household Head	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Schooling	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Health Problems	-0.040***	-0.040***	-0.040***	-0.040***	-0.040***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Household size	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employed as reference					
- *Unemployed*	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
- *OLF*	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married as reference					
- *Divorced*	0.001	0.000	0.000	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
- *Widowed*	0.005	0.005	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
- *Single*	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Acceptable HQ as reference					
- *Recoverable HQ*	-0.003	-0.003	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
- *Unrecoverable HQ*	0.006	0.006	0.006	0.006	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Coast	0.004	0.004	0.004		
	(0.004)	(0.004)	(0.004)		
Density	0.172**	0.179***	0.179***	0.169**	0.170**
	(0.070)	(0.070)	(0.070)	(0.071)	(0.071)
Observations	19995	19995	19995	19995	19995

Notes: Estimates correspond to the marginal change evaluated at the mean of the variables using an Ordered Probit Model on the probability of SAH = 7.
SE clustered at the city level were used in the Ordered Probit Model, whereas the SE for the marginal changes in parenthesis were computed using Delta Method.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

5.3 Is household income endogenous?

So far, we have analyzed the sensitivity of our results to different measures of earthquake/tsunami intensity and mental health variables. The story behind our models assuming exogeneity of household income is somewhat robust. However, before computing the non-pecuniary costs of the earthquake, it is important to analyze whether household income can be considered as exogenous or not.

In this subsection we formally test for the potential endogeneity of household income. Our instrument is a dummy variable indicating whether the household receives rents from urban/agricultural properties or machinery. Table 7 shows the IV results for our dependent variables using PGA as our preferred intensity measure: columns 1, 2 and 3 show the results for our continuous DTS variable using a Two Stage Least Squares (2SLS) model, the prevalence of PTSD using an IV-Probit and the SAH variable using an IV-Ordered Probit model, respectively.

Table 7 Instrumental variable estimation (PGA)

	(1) *DTS (2SLS)*	(2) *Prevalence (IV-Probit)*	(3) *SAH (IV-Oprobit)*
Log of Household Income (USD)	1.099	0.108	0.297***
	(3.243)	(0.172)	(0.094)
PGA	-122.407***	-5.516***	-0.765**
	(16.868)	(0.756)	(0.364)
F/Wald first stage	287.3	287.5	287.5
H_0: Income is exogenous	0.141	0.00000276	3.070
p-value	0.708	0.999	0.0797
H_0: Instrument is valid	0.141	0.00000275	2.992
p-value	0.708	0.999	0.0837
Observations	20055	20055	20055

Notes: For the models estimated by the Maximum Likelihood procedure, such as the IV-Probit and IV-Ordered Probit model, the weak-instrument test is carried out by testing whether the instrument is significant in the reduced equation which is estimated jointly with the mental health equation. Since our model is just identified, the χ^2 statistic is approximately similar to the F-statistic. For the 2SLS, the exogeneity of income is tested using Wooldridge (1995)'s robust score test. For the IV-Probit and IV-Ordered Probit model the exogeneity test corresponds to $H_0 : \rho = 0$, where ρ is the correlation between the error terms of the mental health's and income's equation.
SE clustered at the city level in parenthesis.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

The first test we conduct is whether our dummy variable is a good instrument. The bottom of Table 7 presents the F- (for the 2SLS model) and χ^2-statistic (for the IV-Probit and ordered Probit models) for the reduced equation.[25] The statistics show that our instrument is very powerful, as the

[25] For the models estimated by the Maximum Likelihood procedure, such as the IV-Probit and IV-Ordered Probit model, the weak-instrument test is carried out by testing whether the

F-test and χ^2-test statistics are very large. Furthermore, the overidentification restriction tests show that we cannot reject the null hypothesis that our instrument is valid at the 5%, that is, our instrument is not directly correlated with mental health.[26] However, there is no sufficient information in the sample that household income is endogenous: for DTS and non-prevalence, the null hypothesis that household income is exogenous cannot be rejected, whereas for SAH is weakly rejected.[27] Note that for DTS and PTSD prevalence we do not find any significant effect of household income on mental health, whereas the effect is positive but estimated with less precision for SAH. We argue that this can be explained by the loss of efficiency given that income is not endogenous using these two variables.

The main results do not change even when considering the MMI or tsunami measures as reported in Tables A.3 and A.4. These results are in line with with the argument that endogeneity of income remains fairly limited since income is measured at the household level.

5.4 Compensating variation

Motivated by the previous tests for endogeneity, we select the models without instruments for computing the compensating variation, since they are more efficient under the weak or null evidence that income is endogenous.

To answer the question about the mental-health (or non-pecuniary) costs of the 27-F earthquake we compute two versions of Equation (5). Since the marginal value (MV) depends on the level of income, we must decide on which values of household income to use when computing the compensating variation. The first method uses the average monthly household income before the earthquake, which is approximately \$910 USD, for y_i (see Table 1), whereas the second method computes Equation (5) for each individual and then average over all observations. Both ways yield the same quantitative results, thus we just report the results using average income.

Figure 4 summarizes the compensating variation estimates along with their 95% confidence interval for each measure of earthquake/tsunami intensity and dependent variables. For example, the first panel shows that an average individual should be compensated by \$48,544 USD monthly household

instrument is significant in the reduced equation which is estimated jointly with the mental health equation. Since our model is just identified, the χ^2-squared statistic is approximately similar to the F-statistic.

[26] Here we run the following model:

$$h_{i1}^* = \alpha + \beta \ln(y_{i0}) + \gamma r_i + \mathbf{x}_{i0}'\boldsymbol{\delta} + \lambda z_i + \epsilon_{i0},$$

and test whether $\lambda = 0$. This test has been used to test the validity of the exclusion restriction, i.e., $\text{Cov}(z_{i0} \cdot \epsilon_{i0}) = 0$. See for example Kan (2007).

[27] For the 2SLS, the exogeneity of income is tested using Wooldridge (1995)'s robust score test. For the IV-Probit and IV-Ordered Probit model the exogeneity test corresponds to $H_0 : \rho = 0$, where ρ is the correlation between the error terms of the mental health's and income's equation.

income if PGA increases by approximately one point—holding everything else constant—in order to offset the negative impact on mental health due to the the marginal increase in earthquake's intensity.

Two important points deserve to be noticed. First, a quick look to the graph reveals that the values obtained using either the continuous measure of DTS or the non-prevalence are close in magnitude. This suggests that the MV estimate is not sensitive to the choice between these two variables. Whereas the MVs using the self-assessed health status as dependent variable are much lower. This result can be explained by the fact that SAH is a measure of both physical and mental health. Although the earthquake and subsequent tsunami caused 525 fatalities, an event of such magnitude generates more mental health problems than physical ones in the population (Phifer et al., 1988), and therefore a measure of post-traumatic stress is more suitable to capture such effects.

Second, it is difficult to compare compensatory variations across different intensity measures. For example, consider the MVs obtained using the Probit model on the non-prevalence of PTSD. An one-unit increase of the PGA has an average non-pecuniary valuation of $46,513 (Panel A), while if MMI increases in the same amount the valuation corresponds to $4,846 USD (Panel B). Again, these differences occur since the scales of the intensities are not equivalent in terms of perceived shaking and potential damage. Figure A.2 shows that when we standardize earthquake measures for better comparability, the MVs are much more closer to each other. For example, a one-standard deviation increase in PGA, MMI or PGV is valued in about $2,000 USD when considering the non-prevalence of PTSD. Thus, a preliminary conclusion is that the marginal variations are not sensitive to the intensity measurements used.

The above estimates represent the compensatory variation that average individuals would require if they were exposed to a marginal increase (of about one) in the intensity of the earthquake. Nevertheless, an interesting question that arises is how big is the compensatory variation that should be given to the individuals who were really affected by the earthquake and/or tsunami. To answer this question, we estimate linear and Probit models with the following specification:

$$h_{i1}^{*} = \alpha + \beta \ln(y_{i0}) + \gamma E_i + \phi T_i + \lambda E_i \times T_i + \mathbf{x}_{i0}' \boldsymbol{\delta} + \epsilon_{i0},$$

where E_i and T_i are a dummy variables indicating whether the individual i was affected by the earthquake and tsunami, respectively. Given the results previously obtained, we consider that an individual was affected by the earthquake if PGA is greater than $0.2g$ units, and by the tsunami if there where waves big enough to be disruptive (wave's height> 0.9). Table 8 presents the results for the compensating variation for being affected by the earthquake using Equation (6) evaluated at the mean income (*CV at mean*) and the average across the sample (*Average CV*). Given the interaction term $E_i \times T_i$, the CV for earthquake will depend on whether the individual was also affected by the tsunami.

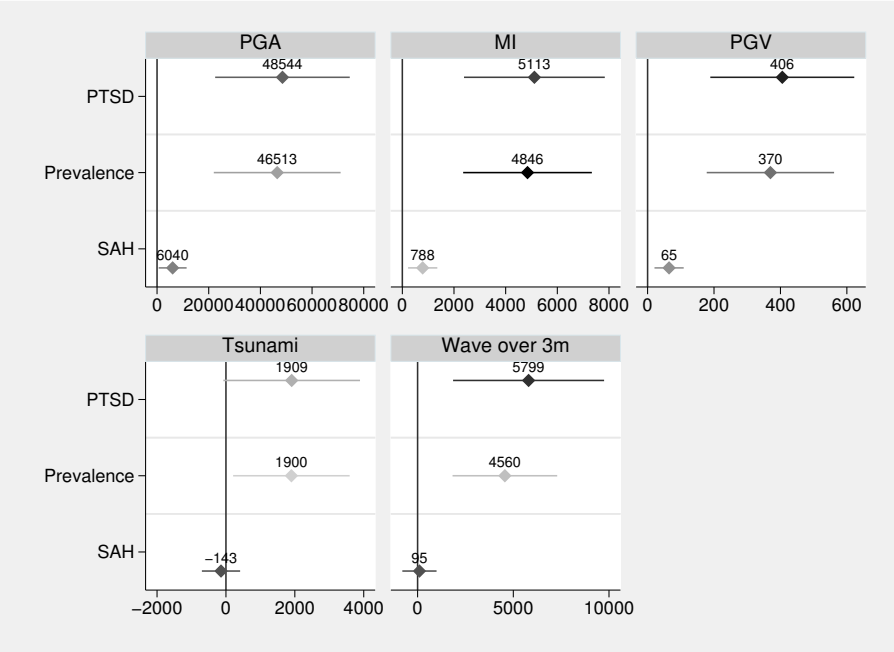

Fig. 4 Compensating variation across models. 95% confidence interval. Compensating variation were computed using Equation (5). SE computed using Delta Method and clustered standard errors. Source: Own elaboration.

Table 8 Compensating variation for being affected by earthquake

	PTSD		No-prevalence	
	(1) *CV at mean*	(2) *Average CV*	(3) *CV at mean*	(4) *Average CV*
Not affected by tsunami	812.098***	826.912***	813.821***	828.667***
	(79.206)	(82.450)	(78.403)	(81.538)
Affected by tsunami	903.297***	854.776***	902.135***	853.676***
	(11.422)	(28.017)	(11.781)	(27.477)
Observations	20055	20055	20055	20055

Notes: Compensating variation were computed using Equation (6).
SE computed using Delta Method and clustered standard errors.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Again, the results show that although compensatory variations are different if we consider DTS or PTSD, these differences are not significant. According to the results for non-prevalence and CV at the mean, those individuals who were exposed to the earthquake, but not to the tsunami, require on average a monthly compensation of approximately $812 USD (89% of household in-

come), while those who experienced both the earthquake and the tsunami need a compensation of $903 (99% of household income).[28]

5.5 Heterogeneity

Finally, we assess the potential heterogeneity of the CV using Equation (6) evaluated at the average monthly household income across age and gender. Figure 5 plots the point estimates for being affected by the earthquake (using our previous dummy variable based on the PGA) at different ages and over gender. In order to save space, and based on the results using the IV procedure, we only report the OLS results using the inverse of DTS as continuous dependent variable.

As expected, the point estimates of the CV, at any given age, is higher for females than males. However, since the confidence intervals overlap, we cannot say with confidence that they are significantly different. This result is in line with that found in Wu et al. (2016). Another important fact is that the gap between men and women decreases as age increases. This reveals that gender seems to play a minor role in mental health deterioration (for being exposed to the earthquake) when comparing older individuals. As age increases, the CV increases for men, but it slightly decreases for females. However, it should be noted that the change in the required income at older ages is not economically significant.

5.6 Discussion

Do our estimates make sense? Rehdanz et al. (2015) use a happiness approach to analyze the effect of the Japanese Great East earthquake/tsunami (2011) on individuals' well-being, finding that the average monetary equivalent of not living in a municipality affected by the tsunami is about $1,700,000 yen (or approximately $15,000), which corresponds to 72% of a person's annual average income. Similarly, Ohtake and Yamada (2013) estimate the monetary value of earthquake news for people in Sendai in about 70% of monthly income per capita when front pages of newspapers were completely filled with negative news. The applied literature also offers CV estimates for other natural disasters or extreme events. For example, Danzer and Danzer (2016) assess the long-run (20 years) effect of the Chernobyl catastrophe in Ukraine. In general, they find strong evidence that there exists a long-run effect of the Chernobyl disaster on subjective well-being and objective mental health. They calculate the monetary compensation necessary to off-set the welfare loss yielding to 31-75% of average monthly household income using an instrumental variable approach. Luechinger and Raschky (2009) find that the average CV for the

[28] Table A.2 shows that the estimates of the compensatory variations are not sensitive if we consider that the individuals affected by the earthquake were those who experienced an intensity equal to or greater than 6.5 on the MMI scale.

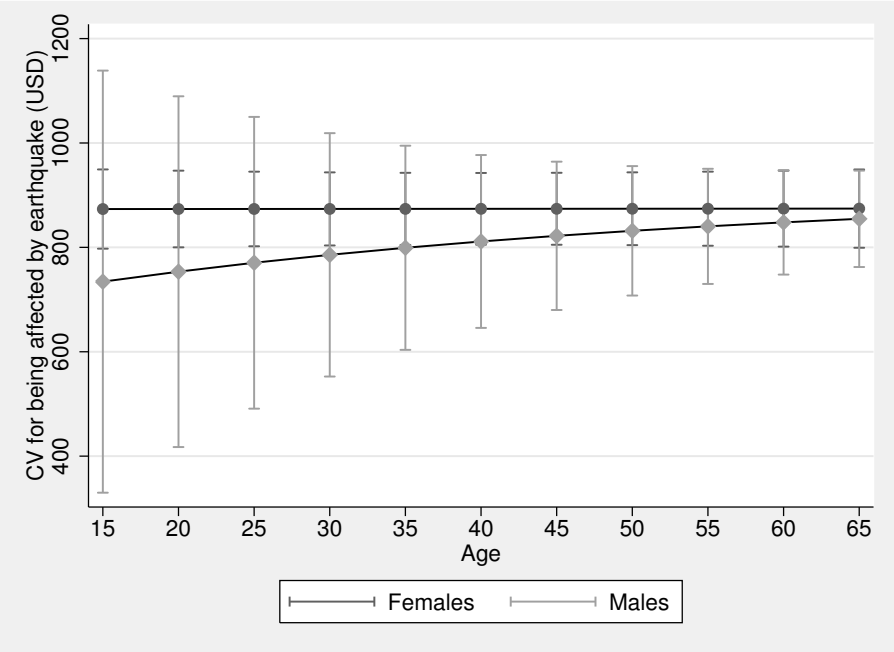

Fig. 5 Heterogeneity of compensating variation for age and gender. 95% confidence interval. Compensating variation were computed using Equation (6). SE computed using Delta Method and clustered standard errors. Source: Own elaboration.

avoidance of one certain flood event is about 24% of average annual household income. Given that our estimates are based on measures of PTSD taken after 5 months of the earthquake, it is not surprising that our CV estimates are higher than in these studies and should be considered as the short-run effect of the 27F disaster.

Using these estimates we can obtain an approximate measure of the total non-pecuniary cost due to loss of mental health after 5 months of the earthquake. In this regard, the 2010 Chile earthquake was estimated to have cost upward of $30 billion USD. However, this estimate does not consider the non-pecuniary costs due to mental health of such traumatic event. The earthquake, which was strongly felt by nearly 80% of the Chilean population, left 525 fatalities and disrupted the livelihoods of 2 million people, more than 10% of the country's population. Thus, using our estimate of $814 USD, the total cost would be roughly equivalent to $2 billion USD.

6 Conclusions

In this study we have proposed a methodology to empirically assess the monetary value of mental health deterioration due to a natural disaster such as an earthquake and tsunami. Using a framework of subjective valuations rooted

in environmental economics, we estimate that individuals who experienced the 2010 Chile earthquake should be compensated with around 90% of their monthly income to be as well-off as before the shock in terms of mental health. According to our estimates, individuals should start receiving compensations when they experience a significant shock. Depending on the measurement units we employ, these thresholds can be interpreted as moderate to heavy damage using either the MMI units ($MMI > 6.5$) or PGA values ($PGA > 0.2g$ units) (Wald et al., 1999).

Our estimates are robust to the definition of impact (PGA, PGV, MMI and Tsunami waves), as well as changes in the dependent variable (PTSD, DTS or SAH), and potential endogeneity issues between the income and mental health variables. We also find that our results are consistent with the findings of similar studies in other countries, adding more evidence that mental-health impacts should also be considered by policy makers in post-disaster scenarios.

Most immediate disaster relief efforts tend to focus on solving major disruptions and medical emergencies, while long-term reconstruction plans tend to focus on infrastructure and prevention strategies. This research shows that post-disaster mental health issues should not be ignored, as these non-pecuniary costs are often absorbed both by individuals and societies (Kessler, 2000). A clear policy implication is that public and private post-disaster efforts should consider mental-health assessments in the short-run, and provide professional help in the mid-run, as local researchers have already suggested (Figueroa et al., 2010). For example, one of the most important public policy lessons this earthquake left for the Chilean government was an updated and unified national policy for disaster preparedness and response. This research's practical implications for this effort is that valuations of mental health impacts make the case for wide psychological and psychiatric treatment policies, since the social returns for such an investment could rival spending on infrastructure on the short-run. Since most of these efforts were done by volunteers after the 2010 emergency, a clear notion of the pecuniary damages could have helped the release of emergency funding for mental health treatments sooner.

There are still possible advances to be done in this strand of research. Even though middle and low income countries have increasingly access to better data, few assessments of large-scale mental health impacts after a disaster have been done in developing regions. Similarly, there are sources of heterogeneity we have not considered in this study, such as religion and social capital. Both have been identified as relevant in this literature, but data limitations have not showed us enough depth in these dimensions to consider them fully. Finally, since the shock was spread across a large geographical space, more insights are needed to grasp spatial heterogeneity within and between regions experiencing catastrophic events.

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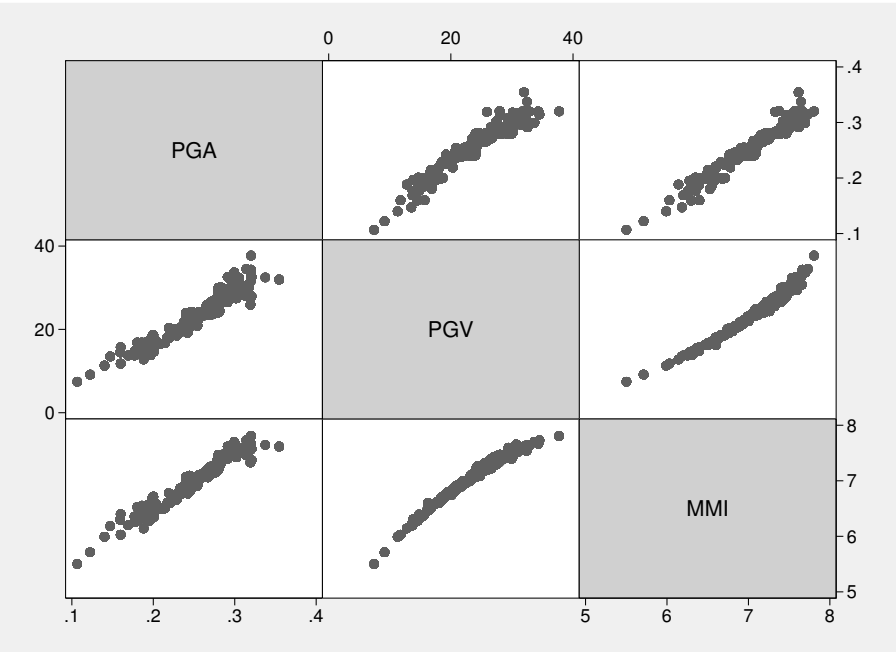
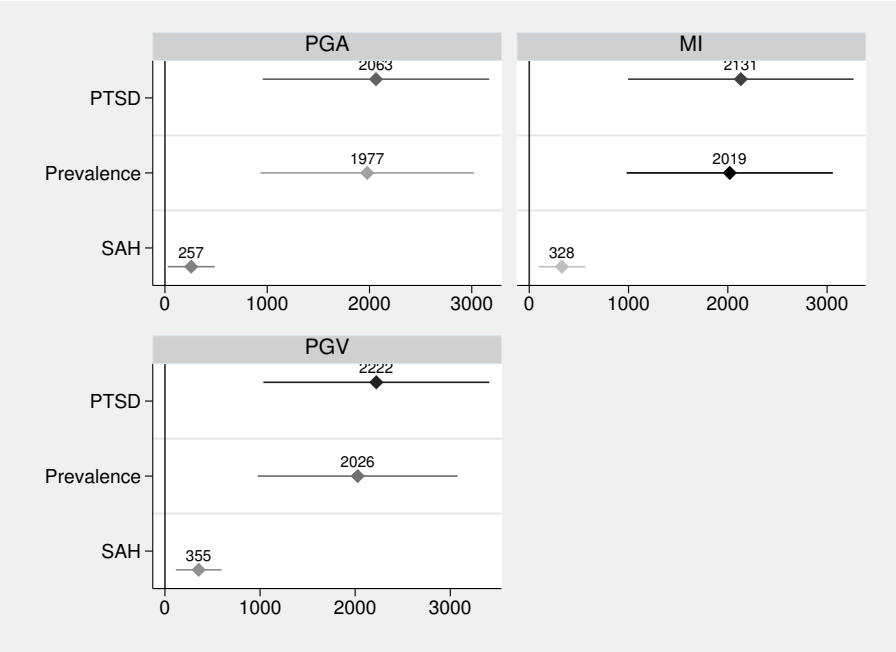
A Annex 1: Additional tables and figures

Fig. A.1 Correlation across PGA, PGV and MMI



Notes: Own elaboration based on USGS shakemaps.

Fig. A.2 Compensating variation across models (one standard deviation increase)



Notes: Compensating variation were computed using Equation (5). SE computed using Delta Method and clustered standard errors. Source: Own elaboration.

Table A.1 Sensitivity analysis for earthquake-intensity measures (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
PGA	-121.768***	276.950*				
	(16.940)	(150.185)				
PGA^2		-827.563**				
		(320.291)				
MMI			-12.547***	91.214**		
			(1.736)	(44.491)		
MMI^2				-7.503**		
				(3.261)		
PGV					-0.969***	-0.255
					(0.134)	(0.984)
PGV^2						-0.016
						(0.022)
Log of Household Income (USD)	1.442	1.381	1.539	1.410	1.514	1.425
	(3.565)	(3.565)	(3.556)	(3.567)	(3.559)	(3.567)
Log of Household Income (USD)^2	0.066	0.064	0.054	0.059	0.052	0.058
	(0.273)	(0.273)	(0.272)	(0.273)	(0.272)	(0.273)
Male	9.033***	9.083***	9.021***	9.079***	9.022***	9.030***
	(0.765)	(0.757)	(0.759)	(0.752)	(0.758)	(0.756)
Age	-0.381***	-0.377***	-0.381***	-0.376***	-0.377***	-0.376***
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Age^2	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household Head	-0.598	-0.545	-0.595	-0.572	-0.601	-0.594
	(0.686)	(0.684)	(0.685)	(0.687)	(0.688)	(0.690)
Schooling	0.358***	0.371***	0.352***	0.361***	0.362***	0.368***
	(0.088)	(0.089)	(0.088)	(0.088)	(0.088)	(0.088)
Health Problems	-6.614***	-6.581***	-6.668***	-6.631***	-6.587***	-6.546***
	(0.918)	(0.904)	(0.922)	(0.912)	(0.911)	(0.908)
Household size	-0.298	-0.287	-0.307	-0.303	-0.298	-0.298
	(0.204)	(0.201)	(0.204)	(0.202)	(0.204)	(0.204)
Employed as reference						
- *Unemployed*	-2.303	-2.219	-2.289	-2.261	-2.289	-2.273
	(1.461)	(1.454)	(1.458)	(1.456)	(1.457)	(1.456)
- *OLF*	-0.083	0.023	-0.077	-0.013	-0.061	-0.044
	(0.638)	(0.630)	(0.640)	(0.635)	(0.638)	(0.639)
Married as reference						
- *Divorced*	0.286	0.254	0.180	0.105	0.125	0.115
	(1.041)	(1.047)	(1.040)	(1.044)	(1.038)	(1.040)
- *Widowed*	-0.006	-0.065	-0.048	-0.108	-0.049	-0.066
	(1.058)	(1.047)	(1.054)	(1.045)	(1.050)	(1.047)
- *Single*	1.824**	1.850**	1.802**	1.836**	1.860**	1.883**
	(0.759)	(0.757)	(0.759)	(0.756)	(0.761)	(0.758)
Acceptable HQ as reference						
- *Recoverable HQ*	-0.527	-0.645	-0.528	-0.597	-0.585	-0.619
	(0.869)	(0.856)	(0.870)	(0.859)	(0.864)	(0.861)
- *Unrecoverable HQ*	-2.007	-2.595	-2.090	-2.594	-2.283	-2.467
	(2.413)	(2.389)	(2.417)	(2.400)	(2.402)	(2.400)
Coast	-2.413	-1.101	-3.058	-2.339	-3.316*	-3.175
	(1.993)	(1.929)	(1.976)	(1.943)	(1.964)	(1.972)
Density	38.522*	28.123	45.544**	35.189	44.795**	41.927*
	(22.480)	(22.839)	(22.746)	(23.251)	(21.795)	(22.553)
Constant	5.399	-41.002**	62.849***	-294.091*	-2.594	-10.058
	(13.118)	(20.437)	(17.049)	(152.157)	(12.628)	(15.851)
Observations	20055	20055	20055	20055	20055	20055
R^2 Adjusted	0.061	0.064	0.062	0.064	0.063	0.064
Turning point for earthquake		0.167		6.079		-8.178
Turning point for age	53.086	53.014	53.172	53.144	53.065	53.032

Notes: Standard errors clustered at the city level in parenthesis.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A.2 Compensating variation for being affected by earthquake (MMI)

	PTSD		No-prevalence	
	(1) *CV at mean*	(2) *Average CV*	(3) *CV at mean*	(4) *Average CV*
Not affected by tsunami	822.509***	837.513***	821.090***	836.068***
	(79.272)	(83.791)	(84.290)	(88.712)
Affected by tsunami	902.096***	853.640***	901.198***	852.791***
	(13.312)	(28.428)	(13.457)	(27.875)
Observations	20055	20055	20055	20055

Notes: Compensating variation were computed using Equation (6).
SE computed using Delta Method and clustered standard errors.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A.3 Instrumental variable estimation (PGA)

	(1) *DTS (2SLS)*	(2) *Prevalence (IV-Probit)*	(3) *SAH (IV-Oprobit)*
Log of Household Income (USD)	1.075	0.107	0.297***
	(3.262)	(0.173)	(0.094)
MMI	-12.619***	-0.565***	-0.100***
	(1.735)	(0.074)	(0.036)
F/Wald first stage	288.7	289.0	289.0
H_0: Income is exogenous	0.133	0.0000388	3.097
p-value	0.716	0.995	0.0784
H_0: Instrument is valid	0.133	0.0000387	3.023
p-value	0.716	0.995	0.0821
Observations	20055	20055	20055

Notes: For the models estimated by the Maximum Likelihood procedure, such as the IV-Probit and IV-Ordered Probit model, the weak-instrument test is carried out by testing whether the instrument is significant in the reduced equation which is estimated jointly with the mental health equation. Since our model is just identified, the χ^2 statistic is approximately similar to the F-statistic. For the 2SLS, the exogeneity of income is tested using Wooldridge (1995)'s robust score test. For the IV-Probit and IV-Ordered Probit model the exogeneity test corresponds to $\mathrm{H}_0 : \rho = 0$, where ρ is the correlation between the error terms of the mental health's and income's equation.
SE clustered at the city level in parenthesis.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table A.4 Instrumental variable estimation (Tsunami)

	(1) *DTS (2SLS)*	(2) *Prevalence (IV-Probit)*	(3) *SAH (IV-Oprobit)*
Log of Household Income (USD)	0.279	0.074	0.295***
	(3.377)	(0.171)	(0.094)
0m < Wave < 3m	1.603	0.046	0.048
	(2.166)	(0.106)	(0.040)
Wave > 3m	-14.957***	-0.556***	0.004
	(3.216)	(0.098)	(0.066)
F/Wald first stage	286.9	287.1	287.1
H_0: Income is exogenous	0.386	0.0475	2.956
p-value	0.535	0.827	0.0856
H_0: Instrument is valid	0.386	0.0474	2.891
p-value	0.535	0.828	0.0891
Observations	20055	20055	20055

Notes: For the models estimated by the Maximum Likelihood procedure, such as the IV-Probit and IV-Ordered Probit model, the weak-instrument test is carried out by testing whether the instrument is significant in the reduced equation which is estimated jointly with the mental health equation. Since our model is just identified, the χ^2 statistic is approximately similar to the F-statistic. For the 2SLS, the exogeneity of income is tested using Wooldridge (1995)'s robust score test. For the IV-Probit and IV-Ordered Probit model the exogeneity test corresponds to $\mathrm{H}_0 : \rho = 0$, where ρ is the correlation between the error terms of the mental health's and income's equation.
SE clustered at the city level in parenthesis.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.001$.

B Annex 2: Derivation of welfare measures

MV can be obtained in the following way. Total differentiation of Equation (1) gives:

$$d\upsilon = \frac{\partial h}{\partial r}dr + \frac{\partial h}{\partial y}dy + \frac{\partial h}{\partial x}dx + \frac{\partial h}{\partial \epsilon}d\epsilon,$$

Setting $d\upsilon = 0$ and holding x and ϵ constant yields:

$$\frac{\partial h}{\partial r}dr + \frac{\partial h}{\partial y}dy = 0.$$

Solving for $\frac{dy}{dr}$ gives Equation (2). Note that in our model income is in logarithm, thus using the fact that $d\ln(y) = dy/y$ yields Equation (5).

Equation (6) is derived as follows. Considering Equation (3) and (4), we get:

$$
\begin{aligned}
h(y_{i0}; r_{i0}; \mathbf{x}_{i0}) &= h(y_{i0} - CV; r_{i1}, \mathbf{x}_{i0}) \\
\alpha + \beta \ln(y_{i0}) + \gamma r_{i0} &= \alpha + \beta \ln(y_{i0} - CV) + \gamma r_{i1} \\
\gamma(r_{i0} - r_{i1}) &= \beta \left[\ln(y_{i0} - CV) - \ln(y_{i0})\right] \\
\frac{\gamma(r_{i0} - r_{i1})}{\beta} + \ln(y_{i0}) &= \ln(y_{i0} - CV) \\
\exp\left[\frac{\gamma(r_{i0} - r_{i1})}{\beta} + \ln(y_{i0})\right] &= y_{i0} - CV \\
CV &= y_{i0} - \exp\left[\frac{\gamma(r_{i0} - r_{i1})}{\beta} + \ln(y_{i0})\right] \\
CV &= y_{i0} - \exp\left[\ln(y_{i0})\right] \exp\left[\frac{\gamma(r_{i0} - r_{i1})}{\beta}\right] \\
CV &= y_{i0} - y_{i0} \exp\left[\frac{\gamma(r_{i0} - r_{i1})}{\beta}\right] \\
CV &= y_{i0} \left[1 - \exp\left[\frac{\gamma(r_{i0} - r_{i1})}{\beta}\right]\right]
\end{aligned}
$$