Household Economic Volatility and the Error of Self-Reported Trauma Data: Results from the 2010 Chilean Earthquake

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Abstract: This investigation examines relationships between economic volatility and trauma by analyzing data embedded in a household survey taken after the February 27, 2010 earthquake off the coast of Central Chile. In addition to investigating these relationships, the internal consistency of the trauma data is investigated and analyzed using econometric and psychometric methods. A general relationship between greater economic volatility and higher incidence of trauma is confirmed, and high comparability is found this scale and other studies which have utilized the same scale. Factor content analysis, however, reveals that a factor accounting for general trauma severity accounts for slightly decreased proportions of the overall variance in total scores as economic volatility increases. This indicates that a degree of systematic error is present when the scale is applied uniformly to a heterogeneous population. Suggestions are offered on how to minimize this error within the theory established on different methods of household survey gathering.

A. Introduction

The 8.8 magnitude earthquake that struck off the coast of Concepción, Chile on February 27, 2010, was one of the largest earthquakes ever recorded on modern equipment. Felt throughout the South American continent, the earthquake devastated communities and caused billions of dollars in direct damages to the region. Many costal Chilean communities were additionally destroyed by the ensuing tsunami. In all, the earthquake caused about $15-30 billion in direct damages to the Chilean economy, or about 10-15% of the country's GDP (EQECAT). However, the damage could have been worse. Seismologists credit Chile's building codes with mitigating the devastation and note that Chile's preparation made recovery a simpler task.

However, direct damages only begin to describe the effects that a large earthquake can have on a community. The indirect damages caused lingering mental disease and Post-Traumatic Stress Disorder (PTSD) cannot be ignored. Smith, Schnurr, and Rosenheck (2005) show for example that a PTSD diagnosis is linked to a higher chance that the victim will drop out of the labor force. Trauma victims are less productive and have a diminished ability to care and provide for their family (Bonanno et al. 2010). A vicious trauma cycle is created because a survivor's level of trauma can be further augmented by these types of stressful periods following a disaster (Norman et. al. 2008). It is thus important to study how trauma is affected by demographic and economic variables both relating to a victim's pre- and post-disaster living situation.

But how do we measure trauma? Clinical trauma data is data gathered by actual doctors giving trauma diagnoses to patients in affected areas. In the absence of this type of rich qualitative data, another method is to directly ask affected populations a standardized set of symptom questions. The benefits of the empirical method of trauma measurement are clear.

Such surveys can hypothetically be given by anyone with limited interview training and can thus be applied to in a timely fashion to a much larger sample of victims. Presumably, this trades an amount of accuracy in measured scores for sample size, but this investigation lacks the clinical data to do any rigorous comparative experiments between the two. However, what I can do with this data is look for inconsistencies and systematic error that can be theoretically minimized through specific survey-taking methods and survey nonresponse minimizing strategies. The data I use in my empirical analysis comes from the Chilean Ministry of Social Development. The observations comprise a two-period panel household survey that was collected 3-4 months before and after the earthquake, and samples 22,456 households in the affected regions of Valparaiso, Metropolitana, O'Higgins, Maule, Araucanía and Biobío. While the data includes many variables that will be used to measure economic volatility in various ways, it also includes a nonclinical, standardized measurement of victims' trauma. The purpose of this investigation is to evaluate the relationship between reliability of self-reported trauma data and economic volatility. The particular scale used in this investigation was originally constructed and questions were chosen in a way that maximizes the reliability and validity of the scale. However, previous applications of this scale do not share the large sample size and heterogeneous population that this data does. This presents a cultural and statistical problem, as different subsets of people may respond to being asked to fill out a survey differently. This investigation assesses the internal consistency of this particular application of the scale to Chile, and questions the validity of applying a scale to such a stratified and demographically diverse population. Do the same relationships predicted in the seminal papers on this scale hold up when applied to such a large population of earthquake victims? Is there any evidence of lost consistency within the data among different subsets of the population?

To answer these questions, the investigation is done in two parts. The first seeks to replicate the findings of previous economic-related trauma studies that draw a relationship between greater household economic volatility and higher incidence of trauma (Neria et al. 2008). The second part of the investigation is an empirical examination of the consistency of the nonclinical self-reported trauma scale embedded in the household survey. Here, I will explore particularly how the reliability and validity of this scale is affected by the economic status of individuals most affected by the earthquake. The conclusions will help in the identification of post-disaster populations with higher risk of trauma, and will quantify problems with internal consistency in such types of self-reported trauma data.

B. Literature Review

A worldwide increase in the number and severity of natural disasters has recently sparked new interest in studying macro and microeconomic consequences of such events (EM-DAT). On the macroeconomic scale, there is a continuing debate over what, if any, effects natural disasters have on a country's overall short and long-term growth. While it is true that natural disasters often have a devastating effect on a country's infrastructure, it should be also noted that disasters often have stimulative economic effects in the short run because of greater demand for construction and manufacturing workers. On the microeconomic scale, natural disaster literature usually focuses on how to mitigate personal and household economic and psychological effects of a natural disaster. The entirety of the damage caused by a natural disaster cannot be solely attributable to direct, physical damage losses. The indirect costs, costs that are caused by a loss of productivity and from an psychologically strained workforce are not as easily measured as the direct damage estimates, but can have just as large of an impact on the recovery of a community.

These indirect costs are affected by the incidence of traumatic diseases like PTSD, which is why the accurate identification of at-risk populations is so important.

Research into the macroeconomic effects of natural disasters has largely concluded that natural disasters on the whole act as stimulative events. Skidmore and Toya (2005) analyze empirically the effects of natural disaster and find that countries with higher quantities of natural disasters on the whole experience higher rates of growth. They find evidence that human capital accumulation in these countries is actually higher overall after a natural disaster, due to a substitution of investment from physical to human capital. Disasters also necessitate frequent technological updates of physical capital, leading to quicker adoption of new technologies and more frequent improvements in physical capital productivity. Albala-Bertrand (1993) finds that physical capital loss in a natural disaster has negligible effects on long-term growth of output. He concludes that macroeconomic responses to natural disaster should be deemphasized in favor of individual household support. Cavallo and Noy (2010) examine the mechanisms behind natural disaster responses, and identify a few factors that dramatically affect how a country responds to a natural disaster on the macroeconomic scale. They find that heterogeneous country effects, like size and composition of economy, development, and physical capital exposure, can play a large role in determining the extent of the worst effects. Finally, Stromberg (2007) finds that a country's political economy can play a role in the mitigation of disaster effects, as countries with well-developed democracies will inevitably be able to enact more effective policies in response to disasters. While demographic and country-fixed effects can play a role in the determination of damages, macroeconomic research has generally established that natural disasters have negligible to positive long-term effects on a country's output, with certain factors augmenting or diminishing the effect.

When moving from a macroeconomic to a microeconomic perspective, it is important to identify sources of heterogeneity not just in country institutions, but also in demographics and exposure within natural disaster populations. The first distinction to make is one about the heterogeneity of natural disaster types. Different types of natural disasters can have very different effects based on the type of exposure experienced by affected populations. Floods, for example, can have a much larger detrimental effect on agricultural communities and, as Carter et al. (2007) finds, hurricanes and droughts can have disproportionate long-lasting negative effects on poor populations, leaving them in persistent poverty traps. Additionally, Mueller and Quisumbing (2010) demonstrate empirically that one should not treat the effects of an individual disaster homogenously, as their study finds evidence that long-term income responses were negatively correlated with height of floodwaters in Bangladesh's 1998 flooding. Finally, one must anticipate the *ex-ante* preparation of the affected countries. As mentioned by Cavallo and Noy (2010), one of the main reasons that Haiti suffered drastically higher physical losses after its 2010 earthquake than Chile's 2010 quake despite Chile's being dozens of times more physically intense was partly because Chile was so much more accustomed to and thus much more prepared for an earthquake of that magnitude. For example, even when controlling for physical differences between the two quakes (distance, depth, other earthquake characteristics) it has been estimated that a person affected by the Hatian earthquake was 400 times more likely to die than a person in Chile. This was primarily a result of Chile's advanced building codes that emphasize earthquake preparedness (Applegate 2010).

A second source of heterogeneity is to look at individual communities and their *ex-ante* and *ex-post* coping mechanisms. Microeconomic studies concerned with household effects of natural disasters (ex. Hall (1978); Foster (1995); Baez and Santos (2007)) incorporate discussions of household infrastructure durability (walls, floor, etc.), job mobility, primary source of income, and other developmental indicators into their respective analyses. Jensen (2000) finds that children of agricultural families suffered lower post-disaster school enrollment and higher post-disaster malnutrition than children in households with other primary sources of income in Cote d'Ivoire from 1985-1988. Foster (1995) finds that a well-defined credit market, or the ability of a parent to find temporary post-disaster income, is a large determinant of *ex-post* child health outcomes.

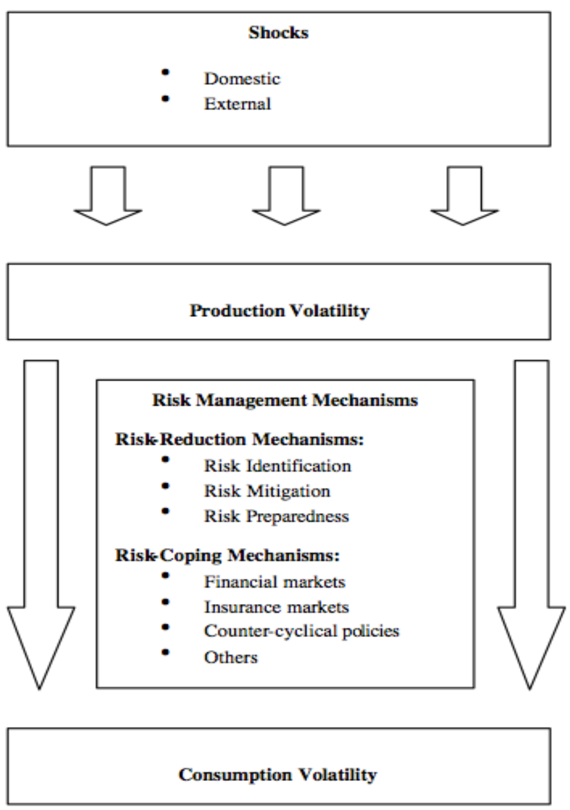
Next, it is important to identify the Kaldor-Hicksian efficiency framework behind the economic connection between mental health and financial volatility. For simplicity, this investigation assumes that higher overall utility, both on an individual and overall basis, is related to lower trauma. This assumption is a large one, but excluding it raises questions that are not within the scope of this paper.[1] If one accepts that the goal of a microeconomic natural disaster response is to maximize the overall utility of the affected population, then the theoretical framework for this analysis can be characterized as one of reallocating resources based on highest marginal benefit. This point is illustrated more completely by an application of Milton Friedman's 1956 Permanent Income Hypothesis (PIH). The PIH is a theory of individual consumption that states that consumption choices are made based on long-term changes to income. Within this theory is the conclusion that temporary changes in income have little effect on consumption changes. In case of a shock to income, consumers can use various financial strategies like loans, remittances from abroad, a new job, or insurance to make up for their lost income and 'smooth' their consumption over the period. Natural disaster consumption smoothing literature (ex. Mohapatra (2009); de Janvry (2004); Baez and Santos (2008)) seeks to

[1] Weehuizen (2008) gives a more comprehensive discussion of mental capital and the importance of mental health to an individual's utility and labor outcomes. This is an emerging field within health economics in which relationships are not yet fully explored.

extract relationships between health, education, or labor outcomes and availability of various *ex-ante* and *ex-post* household income smoothing mechanisms like remittances, credit, and diversity of income. Townsend (1994), for example finds evidence that those who do not own land in Indian villages are less insured against consumption shocks overall than their landed counterparts.

This investigation is primarily concerned with the microeconomic household outcome effects of the 2010 Chilean earthquake, so it is first necessary to define in more detail the progression from an income shock, through income loss mitigation strategies, to consumption volatility. Figure 1 is a theoretical flow diagram of the mechanisms behind *ex-post* natural disaster consumption volatility presented by Phillippe Auffret (2003).

Figure 1: Philippe Auffret's Simple Model of Post-Disaster Consumption Volatility



The figure shows how an external shock, through a shock to an individual's income/production, can determine how a household's level of consumption is affected in the *ex-post* period. The connection between a physical shock and income/production volatility contains research that explores disparate income responses, both short and long term, to a natural disaster. For example, Quisumbing (2010) and Carter (2007) investigate the heterogeneous effects of natural disasters on individuals with different amounts and sources of income. The mechanism behind the connection between production and consumption volatility is the basis for Friedman's Permanent Income Hypothesis and consumption smoothing theory discussed earlier.

The final literature relevant to this investigation is found in literature that explores the actual clinical psychological determinants of trauma. Up to this point, this review of literature has mainly focused on the utilitarian microeconomic connection between economic volatility and consumption decisions. However, the investigation would lack a fundamental link without a discussion of the clinical psychological studies that have explored the factors that determine incidence of trauma in post-disaster populations. In a survey of trauma literature related to natural disasters, Neria, Nandi, and Galea (2007) find that incidence of PTSD after a natural disaster is not solely determined by the intensity of the natural disaster, but rather is correlated with a wide range of socio-demographic characteristics and social support factors. Among these factors, the largest determinants include sex, event exposure characteristics (severity/property loss), and individual labor decisions. Additionally, Galea, Tracy, Norris, and Coffey (2008) examined incidence of PTSD following Hurricane Katrina and find that the largest determinants of post-disaster PTSD were gender, financial loss, and posthurricane stressors (lost job, displaced from home, etc.). They also find that availability of post-disaster support systems had a noticeable effect on the course of personal traumatic disorder. Hobfoll, Tracy and Galea (2006) examine incidence of PTSD after the terrorist attacks of September 11, 2001 and find that an individual's demographic characteristics, prior trauma history, post-disaster social support, and financial loss were all determinants of incidence of PTSD following the disaster. In a study examining the dependency effects of trauma, Abramson and Garfield (2007) find that in regions in the Southern United States affected by Hurricane Katrina, 62% of caregivers scored low on a post-disaster standardized mental health score. Additionally, 13% of caregivers self-reported that they were not coping well with the daily demands of parenting (14% for women, 10.7% for men), a figure eight times higher than similar regions before Katrina. I conclude that the psychological side of research on traumatic stress disorders has found evidence to support the claim that incidence of trauma is largely affected by a few measurable factors including demographic characteristics, income/production volatility, and post-disaster financial and emotional support systems.

C. Data

In the following statistical analysis, I use a two-period household panel survey gathered in mid-2009 and mid-2010 in the regions most affected by the earthquake. Chile's National Survey of Socioeconomic Characterization (CASEN) is a longitudinal survey gathered every 2-3 years in all of Chile's provinces. The survey includes questions of income, occupation, and personal characteristics, similar to the United States American Community Survey (ACS). The last time the full survey was gathered was in 2009 (CASEN 2009). In 2010, the 2009 survey was combined with a separate survey gathered a few months after the earthquake. These two surveys, with households mapped between the two periods, comprise the Post Earthquake Survey

(EPT 2010). The 2010 data includes data on mental health and post-quake education/labor decisions and is a valuable resource in for research on the effects of natural disasters.

The trauma data contained within the EPT 2010 is standardized according to the Davidson Trauma Scale (DTS). The DTS was first proposed and constructed by Davidson et al. (1997). The purpose of the scale is to satisfy a need for a PTSD self-assessment scale that can be applied to a broad sample of trauma victims. The scale includes 34 multiple choice symptom questions, 17 for frequency of symptoms and 17 for severity (See Appendix 1). Respondents are asked to rate their symptoms on a scale from 0-4, 0 being lowest frequency/severity and 4 being the highest. Adding these 34 numbers gives a score out of 136, but this score can be broken down easily first into frequency and severity scores and second into three distinct cluster scores, identified in Appendix 1. Davidson identified threshold scores of 0, 15, 20, and 67, which correspond to no PTSD, weak PTSD diagnosis with no impairment, weak PTSD diagnosis with impairment, and full PTSD diagnosis respectively. Davidson compares his data to clinical data and finds that a score of 40 is the most likely threshold for a diagnosis. See Appendix 1 for further discussion of the scale, including comparisons between the reliability of the EPT 2010 data and other applications of the scale.

One piece of the model uses seismologic data from the United States Geological Survey to generate average intensity data for each commune (third level administrative division) in the survey. This was achieved by overlapping a vector map of the region with coordinates and intensity (peak ground velocity) with a political map of Chile in a GIS program. The average intensity measure for each commune was then matched to each person in the survey based on his or her pre-quake commune. This commune-level exposure variable is not perfect, but it is as detailed of an intensity measure achievable with the data.

Table 1: Descriptive Statistics, EPT 2010

Industry (Pct of labor force)	Female			Male		
	2009	2010	Pct Change	2009	2010	Pct Change
Agriculture, Forestry, Fishing	14.6%	8.7%	-40.62%	30.0%	27.0%	-10.00%
Mining	0.3%	0.4%	22.92%	3.5%	3.3%	-4.44%
Manufacturing	6.6%	3.9%	-40.59%	10.3%	9.9%	-3.63%
Public Works	0.3%	0.2%	-31.00%	1.2%	0.9%	-24.87%
Construction	0.7%	0.8%	24.19%	12.8%	14.2%	10.96%
Commerce	28.2%	28.0%	-0.66%	13.5%	13.1%	-2.87%
Transportation	2.5%	2.5%	1.49%	9.1%	9.2%	1.12%
Finance	4.2%	5.1%	22.53%	4.5%	6.0%	31.53%
Other	42.0%	46.6%	10.95%	14.4%	13.9%	-2.90%
Personal Characteristics	Female			Male		
	2009	2010	Pct Change	2009	2010	Pct Change
Urban living	71.0%	-	-	65.7%	-	-
Married	-	46.7%	-	-	51.0%	-
Working	29.5%	27.2%	-7.8%	63.3%	60.3%	-4.7%
Completed basic education	68.9%	-	-	68.0%	-	-
DTS Severity Score	-	8.87	-	-	5.19	-
DTS Frequency Score	-	9.05	-	-	5.30	-
DTS Overall Score	-	18.2	-	-	10.72	-
Poverty/Housing Variables	Household					
	2009	2010				
Household Income Per Capita	98,503	94,822				
Percent Below Poverty Level	15.5%	17.4%				
Heavy Damage	-	3.30%				
Moderate Damage	-	8.20%				
No/Light Damage	-	88.40%				
Crowded Quarters	-	16.5%				
Exposure Variables	Commune Avg.					
	2010					
Coastal Community (tsunami)	18.2%					
Peak Ground Velocity (cm/s)	21.2					

Descriptive statistics for relevant variables from the data are displayed in Table 1. The sample used in this figure is the subset of the survey that answered the trauma questions. Notice how the expected industry movements away from agriculture and towards more manual labor jobs like construction. The workforce shrunk by about 5-7%, but women suffered more dropouts from the labor force. Also notice the large absolute difference between observed trauma scores for men and women. Women scored on average 7-8 points higher on the overall scale then their male counterparts.

D. Methodology

The first part of the investigation is an OLS regression of the form:

$$O_i = \alpha_0 + \alpha_i X_{i,t=2009} + \beta_i\left(Y_{i,t=2009} - Y_{i,t=2010}\right) + \gamma_i Z_{i,t=2010} + \partial_i T_i + \varepsilon_i \qquad (1)$$

where O_i is a respondent's score on the trauma scale after the earthquake, X_i are demographic controls from the 2009 data, $Y_{i,t=2009}$-$Y_{i,t=2010}$ are the changes between certain variables between 2009 and 2010 for individuals, $Z_{i,t=2010}$ are post-quake (2010 data) variables, and T_i is a collection of treatment variables. T_i is either a collection of mutually exclusive province dummy variables or exogenous shock variables for average commune earthquake intensity. Variables that are included in $X_{i,t=2009}$ are sex, age, urban/rural status, and whether or not an individual has completed basic education (12 years). Variables that are included in $Y_{i,t=2009}$-$Y_{i,t=2010}$ are change in household per capita income between the years, change in poverty status, change in marital status, and change in employment status. Variables included in $Z_{i,t=2010}$ include objective measures of damage to an individual's house and physical crowding in dwellings. Standard errors are heteroskedastic robust.

Next, the investigation assesses the two psychometric properties of the trauma data, its reliability and factorial validity, and compares these results to other papers that have assessed the DTS. In addition to the comparisons, the other purpose in assessing these properties is to question how they are affected by economic volatility. Consider that the observed score on the scale can be modeled as:

$$O_i = T_i + e_i \tag{2}$$

where O_i is the respondent's observed score, T_i is the respondent's true score, and e_i is measurement error created by imperfections in the assessment. Additionally, let

$$O_i = \sum_{j=1}^{34} A_j \tag{3}$$

where A_j is an individual's response to the item j on the assessment. Note that Y_j are discrete variables $Y_j \in [1,2,3,4]$ showing how severe a respondent's trauma symptoms are according to answers to multiple-choice assessment items.

The purpose of measuring the validity of a psychometric scale is to reduce the large number of dimensions in the data to a more usable number of factors. To do this, the investigation uses principal component factor analysis (PCA), which is analogous to how Davidson (1997) assessed the validity of his original data in the absence of further testing. At its simplest, PCA attempts to reveal the internal structure of a scale like the DTS in a way that best describes the variance of the data. It is an orthogonal linear transformation that transforms multivariate data to a new coordinate system such that the greatest variance by any projection of the data lies on the first coordinate, the second greatest on the second coordinate, etc. Consider again the observed and true scores mentioned above, and an *i* by *j* matrix of the form:

$$X_{ixj} = \left[A_{i,j} - \mu_j\right] \tag{4}$$

where each entry corresponds to respondent i's answer to item j on the DTS scale. Note that X_{ixj}^{T} is a zero-mean matrix, as the mean of each item has been subtracted from each entry. Next let Σ be the covariance matrix of X:

$$\Sigma = Cov(X_n, X_m) \tag{5}$$

where m and n are different items in the DTS scale corresponding to different columns in X. Next, we can find and order from highest to lowest the eigenvectors of the covariance matrix to determine the number of significant vector components, or factors, within the data. The eigenvector with the highest eigenvalue is the most important factor of the dataset, the eigenvector with the second highest eigenvalue is the second most important factor of the dataset, and so on. The eigenvectors correspond to factors of the form:

$$\begin{gathered} Factor\ 1 = \gamma_{1,1}, A_{i,1} + \cdots + \gamma_{1,34} A_{i,34} \\ \cdots \\ Factor\ 34 = \gamma_{34,1}, A_{i,1} + \cdots + \gamma_{34,34} A_{i,34} \end{gathered} \tag{6}$$

where each factor has diminishing importance to the overall data based on its attached eigenvalue. In the above equation, the γ values correspond to factor loads on each respondent's answer to an item, $A_{i,n}$. We can thus choose the number of factors out of 34 to retain based on the factors with the largest attached eigenvalues. A summary of a PCA performed on the trauma data of the entire sample in the EPT 2010, and a comparison to the PCA in Davidson's original analysis is found in Appendix 2. The investigation extends this PCA theory to different subsets of economically volatile individuals in the aftermath of the earthquake, and determines whether or not the proportion of the variance accounted for by the retained factors changes as economic volatility increases.

As another way of comparing the data to other DTS studies, this investigation will also measure the internal consistency, or reliability, of the trauma data. Internal consistency measures how well a multi-dimensional scale estimates one single dimensional construct. In the case of the PTSD data, the survey is multi-dimensional because it consists of 34 individual items that, when added together, result in a single-dimensional observed variable (PTSD). A way to measure reliability is using a psychometric characteristic called Cronbach's Alpha. Cronbach's alpha is calculated as:

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_{A_i}^2}{\sigma_X^2}\right) \in (0,1) \tag{7}$$

where K is the number of items on the total scale, $\sigma_{Y_j}^2$ is the variance of item j on the scale, and σ_X^2 is the variance of the observed score. My data makes α a particularly good measure of internal consistency because the test contains many different items. The effectiveness of α as a measure of internal consistency is reduced if K is low (Streiner 2003). Applying this equation to the DTS scale, we see that

$$\alpha = \frac{34}{33}\left(1 - \frac{\sum_{j=1}^{K} \sigma_{A_j}^2}{\sigma_O^2}\right) \tag{8}$$

As Cronbach's alpha approaches 1, internal consistency of the data increases. This means that reliability increases, and the observed score O_i is a better measure of the true score T_i.

Table 2: Regression of DTS Score on Three Clusters of Independent Variables

Regression Results

	(1)	(2)	(3)
	DTS Score	*DTS Score*	*DTS Score*
Urban	-0.658	2.286	1.522
	(0.449)	(0.615)**	(0.453)**
Age	0.065	0.102	0.073
	(0.015)**	(0.020)**	(0.014)**
Male	-6.767	-9.311	-6.948
	(0.452)**	(0.638)**	(0.428)**
Completed Basic Education	-2.379	-2.240	-1.951
	(0.575)**	(0.739)**	(0.554)**
Dropped into Poverty	4.417	4.882	3.602
	(0.918)**	(1.310)**	(0.857)**
Lost Job	0.595	1.678	1.098
	(0.791)	(1.181)	(0.747)
Left Marriage	1.112	1.526	0.835
	(1.077)	(1.647)	(1.025)
Income Loss Quintile 2	1.781	1.210	1.730
	(0.646)**	(0.918)	(0.620)**
Income Loss Quintile 3	3.074	3.238	2.835
	(0.729)**	(1.024)**	(0.692)**
Income Loss Quintile 4	1.308	0.632	1.330
	(0.688)	(0.997)	(0.659)*
Income Loss Quintile 5	0.640	2.308	0.890
	(0.664)	(1.021)*	(0.623)
Married (2010)	0.158	-0.098	-0.474
	(0.441)	(0.617)	(0.421)
Working (2010)	-0.593	0.450	-0.046
	(0.509)	(0.715)	(0.485)
Below Poverty Line (2010)	2.927	2.869	2.334
	(0.641)**	(0.860)**	(0.612)**
Heavy Damage	17.401	13.194	9.714
	(1.765)**	(1.731)**	(1.751)**
Moderate Damage	12.672	9.211	8.151
	(0.981)**	(1.198)**	(0.970)**
Crowded quarters	1.383	0.645	1.489
	(0.794)	(0.989)	(0.769)
Peak Ground Velocity		0.517	
		(0.044)**	
Commune on Coast		-1.437	
		(0.702)*	
Constant	12.512	3.809	10.515
	(1.085)**	(1.718)*	(1.071)**
Observations	25227	15586	25227
R-squared	0.08	0.11	0.16

Robust standard errors in parentheses
* significant at 5%; ** significant at 1%

E. Results

Figure 2 displays the results of the regression of a respondent's score on the Davidson Trauma Scale on the relevant factors as discussed above. Notice that four different specifications have been used, three corresponding to a different way of accounting for regional and provincial differences, and the last corresponding to a regression using as a dependent variable the principal component factor calculated in the PCA analysis which will be discussed later. In the first, no attempt has been made to differentiate between regions or provinces. In the second, two variables were added that attempt to measure the strength of an exogenous shock that individual communes faced. The first is commune (126 communes in sample) average peak ground velocity for the earthquake, and the other is a binary variable for whether or not the commune is on the coast and potentially experienced a tsunami. Peak ground velocity is a better measure than peak ground acceleration for large intensity earthquakes, so it was used here. The third regression is a fixed-effects model with 26 mutually exclusive provincial variables.

In the first group of variables, notice the effect that 2009 demographic variables have on a respondent's score. Urban dwellers scored between 1.5 and 2.5 points higher on average and scores increase about .06 per additional year of age. Males scored on average around 7-9 points lower than females and skilled workers scored around 2-2.5 points lower. Notice that in all three regressions, most of the variables that were calculated as changes between 2009 and 2010 have statistically significant positive coefficients. If someone dropped below the poverty level, they on average scored 3-4 points higher on the scale. If they lost their job, they scored on average about 1 point higher.

Some further interesting results are the coefficients on income loss. These coefficients are not strictly decreasing or increasing as quintile increases, but yet are still positive and statistically significant in almost all cases over the first quintile (which was omitted due to multicollinearity). These coefficients, however, pale in comparison to the coefficients on heavy to moderate damages. If a respondent's house was moderately or heavily damaged, my regressions indicated they scored between 10-15 points higher on the scale. In the second regression, note the positive and statistically significant correlation between increasing earthquake intensity and score.

Table 3: Principal Component Factorization of DTS Scale for Different Subsets of Volatile Respondents of the EPT 2010

Factor Analysis

	Factor						Combined
	I		**II**		**III**		**I+II+III**
	Porportion of Variance	Eigenvalue	Porportion of Variance	Eigenvalue	Porportion of Variance	Eigenvalue	Cumulative Variance
Income Loss Quintile							
Q1	50.44%	17.15	6.11%	2.01	5.16%	1.75	61.71%
Q2	51.89%	17.64	6.06%	2.06	5.15%	1.75	63.10%
Q3	52.46%	17.83	6.00%	2.04	5.25%	1.79	63.71%
Q4	52.33%	17.79	5.83%	1.98	5.02%	1.70	63.18%
Q5	53.44%	18.17	5.79%	1.96	4.89%	1.66	64.12%
Fell into Poverty							
No	52.07%	17.71	5.96%	2.03	5.07%	1.73	63.10%
Yes	51.97%	17.67	5.63%	1.91	5.12%	1.74	62.72%
Below Poverty Line (2010)							
No	51.83%	17.62	5.93%	2.02	5.03%	1.70	62.79%
Yes	52.85%	17.96	5.98%	2.03	5.28%	1.80	64.11%
House Crowding							
None	51.93%	17.66	5.93%	2.02	5.08%	1.72	62.94%
Medium	53.49%	18.18	6.01%	2.04	4.95%	1.68	64.45%
Severe*(n=286)	52.13%	17.73	6.80%	2.31	5.98%	2.03	64.91%
House Damage							
Low/None	50.71%	17.24	6.07%	2.06	5.21%	1.77	61.99%
Moderate	50.77%	17.26	5.95%	2.02	5.61%	1.90	62.33%
Heavy	55.20%	18.77	6.04%	2.05	4.45%	1.51	65.69%
Lost Job							
No	51.82%	17.62	5.92%	2.01	5.11%	1.73	62.85%
Yes	53.57%	18.21	6.13%	2.08	4.93%	1.67	64.63%
Gender							
Male	51.11%	17.37	5.66%	1.92	5.30%	1.80	62.07%
Female	51.81%	17.61	6.05%	2.06	5.11%	1.73	62.97%

Table 3 displays the results of the primary component factor analysis for selected subsets of the data. Only three factors were retained in each group, based on identifiable characteristics of those factors, as described in Appendix 2. Factor I always takes up between 50-55% of the variance, and it is clear from this table that the proportion of variance accounted for by the first factor increases marginally as economic volatility increases. To make this happen, the eigenvalue of the covariance matrix attached to the first factor in each situation must increase as volatility increases as well.

Notice the strange result on factor 2, notably that there seems to be an inverse relationship between the proportion of the variance taken by the first factor and the proportion of the variance taken by the second factor. It is impossible to establish causation here, so the investigation stops at an identification of the trend. It is also hard to extract a trend from the third factor. No relationships are immediately apparent. The cumulative variance accounted by these first three factors shares the positive relationship between economic volatility and greater share of variance.

F. Conclusion

This investigation has thus answered the questions that it sought to answer. Using household survey data from before and after the 2010 Chilean earthquake it has replicated findings of previous studies that have identified a relationship between economic volatility and trauma, and has extended upon psychometric literature that examines the reliability and validity of self-reported trauma data. I found that demographic variables like sex, income, and education each have a statistically significant effect on a victim's intensity of traumatic disease. Stressful events like a lost job or lost marriage in the post-quake period also have large effects on trauma scores. Through the application of the psychometric techniques of factor content analysis and

Cronbach's alpha, I determined that the Chilean trauma data is on the whole both reliable and relatively consistent with results found in other applications of the scale. This in itself is interesting because it shows that reliability of the DTS as a trauma measure is relatively unaffected by the heterogeneity of the population to which it is applied. However, in spite of the overall reliability and validity of the data, the investigation found a minimal degree of systematic inconsistency in the data when these methods were applied to different volatility subsets of the Chilean victims. The proportion of the variance accounted for by the first factor in a principal components factorization seemed to increase as economic volatility increase. The differences were small, but certainly warrant further study on the application of a trauma scale of this type to a heterogeneous population of disaster victims.

So what can we take away from this? Qualitatively, I believe this is a survey-taking problem. Richer, less economically volatile victims may have more free time with which to spend filling out a survey and answering every question honestly. In essence, their opportunity cost of spending time answering questions on a survey may be lower than the opportunity cost of poorer, more volatile victims. Groves and Heeringa (2006) notes that over the last few decades there is evidence that people are more reluctant to dedicate the time to filling out surveys than ever before. It is plausible then that this reluctance could be affected by a person's economic status. A more volatile victim may have a higher chance of just assigning a singular value to each question in the interest of completing the survey quickly, where a less volatile victim may consider each question in more depth. It is easy to see how this would contribute to a scale that is more one-dimensional for higher volatility subsets. Groves and Heeringa (2006) further suggests a few further methods one could use to motivate individuals to be more responsive to surveys, including ways to guide survey takers within the time that the survey is taken to maximize genuine response and minimize non-response. Couper and Groves (1998) expand further on the opportunity cost argument of survey nonresponse and find minimal empirical evidence for the theory. One of the reasons for this, however, is that it was hard to find a factor that accurately describes the time constraints faced by survey participants, let alone to identify constraints that are uniform to all participants. In the case of Chile, this factor is easily identifiable, because all respondents went through the earthquake and suffered disparately. Thus, I think the opportunity cost hypothesis is plausible here.

As a solution, Couper and Groves (1998) suggest that models that accept nonrandom error should be considered. The goal of their chapter is to minimize nonresponse error, and they identify a few characteristics that do just that. First, they suggest making an attempt to offer an array of surveys in a way to minimize nonresponse error. For example, some incentives could be introduced to create more consistent data within economically volatile populations. Second, interviewer training is important, as the success of survey data depends highly on the immediate interaction between the survey taker and respondent. This requires the interviewer to have a high level of social capital and knowledge of the customs of many different types of people in many different cultures. Third, promotional materials could be used as tools to motivate certain subsets of a population to respond more accurately or completely. It should be noted that these theories stand in almost direct contradiction to traditional sampling methods. In essence, the assumption that a survey taker has a random sample is thrown out in pursuit of more consistent data. However, as Couper and Groves say in their chapter, "Successful interviewers seem to learn that fitting the approach to the sample person is wiser. … Survey participation is influenced by many factors related to the survey request, the survey design, the interviewer, and the householder."

Nonetheless, these results motivate future study of how widely heterogeneous populations fill out standardized surveys. Couper and Groves (1998) have already established a theoretical framework within which consistent data can be gathered. While the systematic error that this investigation found was in effect statistically quite small, this may be because of how impressively reliable of a measure of trauma the DTS is. It has been translated, applied to different cultures and applied to heterogeneous populations with negligible losses to reliability. Thus, the cultural problems that Couper and Groves articulate in their chapter are minimized by design, and by effect the DTS as a statistical tool holds up remarkably well under closer examination.

G. Appendix 1: Davidson Trauma Scale – Structure and Reliability Comparisons

Table A1: Structure and Averages of the Davidson Trauma Scale

Structure and Averages

	Item #	Question	Averages (EPT 2010) Frequency	Severity	Cluster
Intrusive Cluster (max=20)	1	*Have you had painful images, memories or thoughts of the event?*	0.60	0.62	5.14
	2	*Have you had distressing dreams of the event?*	0.35	0.38	
	3	*Have you felt as though the event was re-occurring?*	0.50	0.53	
	4	*Have you been upset by something which reminded you of the event?*	0.71	0.68	
	17	*Have you been physically upset by reminders of the event?*	0.37	0.39	
Avoidance Cluster (max=8)	5	*Have you been avoiding any thoughts or feelings about the event?*	0.48	0.46	1.71
	6	*Have you been avoiding doing things or going into situations which remind you about the event?*	0.38	0.38	
Amnesia and Numbing Cluster (max=20)	7	*Have you found yourself unable to recall important parts of the event?*	0.24	0.24	2.90
	8	*Have you had difficulty enjoying things?*	0.37	0.36	
	9	*Have you felt distant or cut off from other people?*	0.24	0.23	
	10	*Have you been unable to have sad or loving feelings?*	0.22	0.23	
	11	*Have you found it hard to imagine having a long life span fulfilling your goals?*	0.38	0.39	
Hyperarousal Cluster (max=20)	12	*Have you had trouble falling asleep or staying asleep?*	0.63	0.63	5.86
	13	*Have you been irritable or had outbursts of anger?*	0.41	0.41	
	14	*Have you had difficulty concentrating?*	0.44	0.44	
	15	*Have you felt on edge, been easily distracted, or had to stay 'on guard'?*	0.71	0.71	
	16	*Have you been jumpy or easily startled?*	0.74	0.74	
				Average Total Score 15.59	

Table A2: Cronbach's Alpha Comparisons Between EPT 2010, Other DTS Studies

Comparisons Between EPT 2010, Other Davidson Trauma Scale Studies

Study	Sample	n	Cronbach's alpha Frequency	Severity	All
EPT 2010	Earthquake Victims (Spanish)	28,594	0.94	0.95	0.97
Davidson et. al. (1997)	Rape, war, hurricane victims (USA)	241	0.97	0.98	0.99
Chen, Lin et. al (2001)	Earthquake Victims (Chinese)	210	0.93	0.95	0.97
Declercq (2006)	Security company and Red Cross (Belgium)	544	-	-	0.97
Ford-Gilboe et. al. (2009)	Domestic Abuse Victims (Canada)	309	-	-	0.95
Seo, Chung et. al. (2008)	PTSD patients (Korea)	254	0.93	0.95	0.97

Table A1 displays the questions on the Davidson Trauma scale, the associated clusters and their averages, and the total average score for all respondents. The questions on the scale are from the fourth revision of the Diagnostic and Statistics Manual (DSM-IV). Table A2 compares the Cronbach's alpha value from the Chilean EPT 2010 data to those in a few other studies. Note that the particular scale used in the EPT 2010 is the DTS-S, or the Spanish version of the scale. Chen, Lin, et. al., Declercq (2006), Seo, Chung et. al. (2008) use DTS-C, DTS-D, and DTS-K for Chinese, Dutch, and Korean translations of the questions used on the scale. Since Cronbach's Alpha depends on K, the number of items on the scale, the overall alpha will typically be higher than the alpha values for each frequency and severity subsets.

H. Appendix 2: Principal Components Analysis of the Davidson Trauma Scale in the EPT 2010

One of the benefits of applying factor analysis to the Davidson Trauma scale is that the reduced number of factors can be interpreted as measurements in themselves. Davidson (1997) and the table below illustrate how this is possible.

Notice that Factor I, which accounts for over 50% of the variance in scores, has factor loads that are all greater than zero. This is the expected factor that correlates with general increasing trauma, or as Davidson puts it, a "general severity factor". However, notice that the loadings within Factor II (about 5-6% of the variance) are positive or negative based almost entirely on which cluster the item belongs to. This is almost an identical result to Davidson's factor analysis, and he interpreted this factor as being indicative of reduced enjoyment, estrangement, lack of loving feelings, and foreshortened future. Factor 3, 4 and 5 do not share such strict similarities to Davidson's original analysis, but they do not account for very much of the variance anyways.

Table A3: Principal Components Factorization of Full EPT 2010 Sample

	Principal Components Factorization				
	Factor (Full Sample)				
Item #	**I**	**II**	**III**	**IV**	**V**
Frequency					
1	0.75	-0.24	0.15	0.16	-0.07
2	0.69	-0.10	0.22	0.40	0.13
3	0.75	-0.16	0.21	0.21	-0.03
4	0.71	-0.23	0.17	0.09	-0.12
17	0.76	-0.07	0.16	0.05	0.03
5	0.74	-0.09	0.26	-0.30	-0.15
6	0.74	-0.02	0.27	-0.33	-0.11
7	0.59	0.35	0.28	-0.17	0.56
8	0.75	0.14	0.05	-0.15	-0.15
9	0.61	0.45	-0.10	0.13	-0.27
10	0.55	0.59	-0.02	0.26	-0.03
11	0.71	0.19	-0.09	-0.14	-0.24
12	0.74	-0.15	-0.28	0.03	0.08
13	0.73	0.08	-0.31	-0.06	0.09
14	0.77	0.03	-0.30	-0.07	0.11
15	0.78	-0.22	-0.31	-0.03	0.07
16	0.78	-0.23	-0.29	-0.02	0.07
Severity					
1	0.75	-0.23	0.16	0.16	-0.05
2	0.69	-0.11	0.22	0.40	0.13
3	0.75	-0.17	0.21	0.21	-0.02
4	0.75	-0.22	0.18	0.09	-0.10
17	0.76	-0.08	0.16	0.04	0.03
5	0.76	-0.07	0.27	-0.28	-0.14
6	0.76	-0.01	0.27	-0.31	-0.08
7	0.59	0.34	0.28	-0.16	0.57
8	0.77	0.14	0.05	-0.15	-0.14
9	0.63	0.45	-0.10	0.14	-0.26
10	0.55	0.59	-0.02	0.26	-0.03
11	0.72	0.19	-0.10	-0.13	-0.24
12	0.75	-0.14	-0.28	0.03	0.09
13	0.74	0.08	-0.31	-0.05	0.10
14	0.78	0.02	-0.30	-0.07	0.12
15	0.79	-0.21	-0.31	-0.02	0.08
16	0.79	-0.23	-0.28	-0.02	0.09
Eigenvalue	17.73	2.01	1.73	1.17	1.15
Porportion of Variance	52.17%	5.93%	5.07%	3.45%	3.39%

Subjectively, Factor III appears in my data to measure the intrusive and avoidance cluster, IV appears to measure a similar construct, and factor V seems to measure hyperarousal. While the investigation does not include very much rigorous analysis of the second and third factor, their inclusion in this appendix serves to demonstrate how comparable the DTS is between the EPT 2010 survey and other applications of the scale.

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