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1 **Do social adaptations increase earthquake resilience?**

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15

17 **Abstract**

18 Grandparents in earthquake-prone Chile teach children to identify load-bearing walls, and the
19 Philippines has developed an internationally respected disaster management system. Do such low-
20 cost, social adaptations increase community resilience to earthquakes, or are poorer countries forever
21 doomed to large death tolls in small earthquakes? We attempt to answer this question by quantifying
22 the vulnerability of exposed populations to a set of earthquakes recorded in the USGS PAGER
23 system. We first remove the effect of strong shaking by statistically modelling published mortality,
24 shaking intensity and population exposure data; unexplained variance from this purely physical model
25 is dominated by, and its systematics therefore illuminate, the contribution of socio-economic factors
26 to increasing earthquake mortality. We find that this variance partitions countries in terms of basic
27 socio-economic measures and allows the definition of an Earthquake Vulnerability Index, which
28 identifies both anomalously resilient and anomalously vulnerable countries. Unsurprisingly, wealthy
29 countries perform well, while in general poor countries are more vulnerable. However some low-
30 GDP countries rival even the richest in their ability to resist shaking, suggesting that social and
31 political will can increase resilience. Until expensive engineering solutions become more universally
32 available, the objective targeting of resources at relatively low-cost interventions might help reverse
33 the trend of increasing mortality in earthquakes.

35 1. Introduction

36 Earthquakes represent high-impact, low-probability hazards. Their forecasting, despite significant
37 advances in observing, understanding and modelling the physical process, is poorly constrained by
38 current science in both space and time. This compounds the problem of persuading governments to
39 prioritise building earthquake resilience against their response to more focused threats, particularly
40 in the absence of proven, effective and affordable interventions. Consequently, earthquake resilience
41 remains low and earthquake mortality continues to grow exponentially.

42

43 Here, we describe a method to quantify earthquake vulnerability, and use it to identify countries
44 whose resilience to earthquake shaking, despite low GDP, demonstrates the action of ill-defined, low-
45 cost interventions which, if properly understood, might be applied internationally to increase
46 earthquake resilience. We argue that, until engineering solutions become more universally affordable,
47 quantifying vulnerability and thereby identifying evidence-based interventions, could slow the
48 increase in earthquake deaths.

49

50 Globally, population vulnerability to earthquakes is strongly variable^{1,2}; events with similar amounts
51 of shaking produce vastly different outcomes. Here we generalise the idea of earthquake vulnerability
52 to: the set of compound factors which tend to influence mortality in a population exposed to strong
53 shaking. Vulnerability in this context applies to a population as a whole, incorporating a range of
54 interrelated social, geographical and engineering factors. Here, we do not attempt to identify the
55 component influences in the usual way for risk modelling, much less attempt to model them explicitly.
56 We attempt to access the aggregated vulnerability effect by modelling earthquake mortality as a
57 function of hazard and exposure only, and exploring to what extent this fails to explain the mortality
58 data from large earthquakes since 1960. In this sense, we consider a kind of “Mortality Risk”, which
59 we assume to be a separable function of 1) the generalised vulnerability and 2) the geophysical
60 influences of hazard and exposure.

62 GDP undoubtedly has a first order influence on such vulnerability; affluent countries can construct
63 resilient buildings, for example, which undoubtedly is a factor in reducing population vulnerability³.
64 To focus solely on GDP and expensive engineering, however, implies that earthquake vulnerability
65 is “hard-wired” into existing social structures and that nothing short of reorganisation of global wealth
66 can reduce earthquake impact. Clearly this statement requires more careful examination.

67 In 2010 earthquakes of magnitude $M_w=7.0$ and 7.1 respectively shook the cities of Port au Prince,
68 Haiti^{4,5} and Christchurch, New Zealand⁶; both produced similar distributions of modelled strong
69 shaking around their epicentres and neither induced destructive secondary hazards. Haiti suffered
70 more than 200,000 dead, while no one was killed in New Zealand. It is tempting to conclude that the
71 high mortality in Haiti was simply due to poverty, corruption and the lack of robust seismic building
72 codes and enforcement resulting in poor building quality. The commonly quoted, and essentially
73 defeatist, aphorism “earthquakes don’t kill people buildings do”, implies that the only way to increase
74 resilience to earthquakes is the improvement of building stock. High national income indisputably
75 allows the deployment of risk-proof engineering⁷ which reduces vulnerability. But this obvious
76 economic fact does not imply that low-cost social interventions, loosely defined here as non-
77 engineered interventions available to low-income economies – including for example hazard-
78 conscious legislation such as that which underpins the Disaster Risk Reduction and Management
79 system in the Phillipines⁸, or developing tailored earthquake preparedness education for
80 dissemination at sub-national and local levels, for example in curricula for schools⁹ – and which might
81 be available to the world’s poor¹⁰, are ineffective in increasing earthquake resilience. This entirely
82 separate conclusion requires separate investigation.

83 Earthquake fatalities, as opposed to fatalities resulting from secondary hazards such as tsunamis or
84 landslides, are caused by complex interactions between strong shaking and the size and vulnerability
85 of the population exposed to them. We cannot explain the difference in mortality between the Port au

86 Prince and Christchurch events without considering the very different exposure of their populations.
87 If we are to better understand vulnerability, this exposure to strong shaking, which dominates
88 mortality, must, as far as possible, be removed from the analysis. Only then might we identify
89 anomalously resilient communities whose socio-economic structures¹¹ may enhance (or compromise)
90 resilience relative to a reasonable expected outcome conditioned by population exposure to strong
91 shaking and, ultimately, recommend economically feasible interventions.

92 Past analyses of the social dimensions of earthquake vulnerability have been built largely on
93 assessment of exposure based on population distributions relative to earthquake risk¹²; more
94 quantitative studies have been restricted to the physical and engineering dimensions of vulnerability
95 (for example building fragility¹³). Here we develop a quantitative methodology that will access the
96 aggregate vulnerability for populations, which will include the social components.

97 From a purely geophysical perspective (i.e. neglecting both social and engineering influences
98 including building design and construction), an earthquake produces spatially-variable shaking
99 intensities and will be more or less fatal depending on the strength of this shaking and the number of
100 people experiencing it; dangerous earthquakes, like Haiti, produce strong shaking for large
101 populations.

102 Since 2007, the Modified Mercalli Intensity (MMI), a measure of the strength of shaking, is routinely
103 calculated for the area affected by every damaging earthquake and is published together with the
104 number of people estimated to have experienced shaking of different strengths. Hindcasting of
105 earthquake shaking and population densities extends this database back to 1960^{14,15}. Note that, while
106 the MMI scale is defined with reference to, and calibrated against, Mercalli intensity (defined
107 according to damage assessments, which would originally have incorporated local vulnerability
108 implicitly), the PAGER published MMI values are calculated from a physical shaking model which
109 does not take any account of the earthquake's local context. MMI values are therefore akin to an
110 objective, vulnerability-independent forecast/forward-model of damage (which then become the basis

111 of PAGER's full context-dependent damage forecast). The values we use here have therefore no
112 contribution from vulnerability in their calculation, though they use a version of the Mercalli intensity
113 scale.

114 The National Oceans and Atmospheric Administration (NOAA) records the number of fatalities
115 disaggregated by likely cause of death¹⁶. We choose this database since we wish only to consider
116 fatalities caused by strong shaking, though it correlates well with other databases¹⁷⁻²¹ for the study
117 period.

118 **2. Methods**

119 We begin by assuming that the number of people shaken strongly by an earthquake is a first-order
120 control on mortality, and that therefore one indicator of likely mortality is the profile of the number
121 of people estimated to have experienced shaking of different intensities. This is routinely estimated
122 in the PAGER catalogue for every large earthquake globally, and is referred to here as the Shaking
123 Intensity Profile (SIP) for the earthquake. In the absence of any other influencing factors, there would
124 exist a weighting vector, $\mathbf{w}$, whose components, w_k , link the number of people experiencing shaking
125 of a given intensity, k , to the number of deaths (per thousand for example) which might be expected
126 for that intensity; when weighted by $\mathbf{w}$, the SIP could be expected to predict the number of deaths, y ,
127 in the event due purely to the physical effects of shaking, without any socio-economic variability.
128 The predictor for an event i , which we term the shake potency, s , takes the form:

$$129 \quad s_i = \sum_{k=1}^K w_k d_{ik} \quad (1)$$

130 where d_{ik} is the number of people exposed to shaking of Mercalli intensity $k = 1, \dots, K$ (representing
131 some subset of MMI=I, ..., X) and w_k is a weight related to the severity of the shaking at that intensity.

132 If this model is well specified with respect to contributions to earthquake mortality from shaking,
133 then, in a world in which we could accurately measure shaking strength everywhere, in which we

134 knew the precise distribution of population and in which we all lived in identical societies, s could be
135 expected to correlate strongly with earthquake mortality. In other words, provided we have a good
136 estimate of $\mathbf{w}$, we would expect variance in the data associated with the shaking alone (due to, for
137 example, errors in the estimates of the SIP) to be purely stochastic.

138 Of course, there is clearly also a large systematic component due to unmodelled, chiefly social,
139 influences on mortality. Since it is not possible to separate out these components, we have chosen to
140 take the empirical approach of optimising $\mathbf{w}$ so that the model, assuming *only* stochastic errors, gives
141 the best explanation of the data possible. This approach should be considered not as an attempt to
142 model the mortality data, but as an attempt to make the data conform as much as possible to our
143 assumed physical model, thereby obtaining a lower limit on the variance attributable to social
144 influences.

145 We have extracted the SIPs together with the number of deaths, y , attributed to strong shaking for
146 each event excluding those resulting in fewer than 10 deaths (giving a total data set of 232 events)
147 and have therefore chosen a truncated Poisson model for the stochastic variance. $\mathbf{w}$ is estimated by
148 maximum likelihood, including contributions from the SIP for $\text{MMI} \geq \text{VI}$. For full details of the error
149 model and optimisation procedures see the Appendix.

150 **3. Results and Discussion**

151 We have plotted the calculated s for each event against y in figure 1a, along with the expected
152 mortality, λ , calculated from the optimised model (see the Appendix), as a function of s .

153 Since we have no real constraints on the likely magnitude of the stochastic variance, we are unable
154 formally to identify events that are not well explained by shaking alone. Insights into the nature of
155 the social contribution to the variance remaining after optimisation must instead come from the
156 identification of systematic social trends within the data. We choose the World Bank assessment of
157 the national per capita GDP as the basic measure of the social status of countries experiencing this

158 shaking²². GDP correlates strongly with other development and educational indices and its wide
159 application in comparable studies makes this a useful proxy indicator of development status for the
160 present high-level study.

161 As might be expected figure 1a exhibits significant scatter. We note that, as expected, countries with
162 high GDP tend to plot in the bottom right quadrant, where even potent earthquakes kill few people.
163 This clearly illustrates that the variance around this model is not purely stochastic and that its
164 systematics are related to socio-economic structures (probably dominated by quality of construction
165 and engineering). More surprisingly, interspersed with the hot colours of USA and Japan are a large
166 number of blue points representing potent earthquakes in poor countries, which killed only few
167 people. Furthermore, the plot also exhibits some national differentiation of resilience among countries
168 of similar GDP. In figure 1b, for example, some relatively low-income countries populate distinct
169 areas of s - y space; the blue circles of earthquakes in the Philippines cluster in the area expected to be
170 populated by rich countries, with two orders of magnitude greater GDP, while many of the blue stars
171 of Iranian earthquakes plot in the upper left quadrant, where less potent events kill great numbers of
172 people, signifying less resilience than would be expected for its GDP. This supports the view that
173 non-physical, non-economic and, at least in part, nationally constrained factors make populations
174 more or less vulnerable to similar levels of shaking exposure. Closer study of the earthquakes
175 represented by these data points might expose local or national interventions which are increasing
176 resilience of communities to strong shaking in the absence of major national investment.

177 We define shake vulnerability for a given earthquake, $\delta_i = y_i/\lambda_i$, to be the ratio of the number of deaths
178 in an event i to the expected mortality due to the shaking in that event, then compute an earthquake
179 vulnerability index $[EVI]_i = \log \delta_i$, for all countries. High (low) values of this measure indicate high
180 (low) vulnerability. A plot of EVI against log GDP (figure 2) shows the expected broad negative
181 trend, indicating a general income-dependence of vulnerability to strong shaking. Countries which
182 are more vulnerable than expected according to this model plot above the best-fit line, while those

183 which are more resilient plot below. It is not the aim of this study to explain the contrasting
184 vulnerabilities exposed in figure 2, however some speculation as to cause might help to illustrate the
185 potential of this analysis.

186 The plot certainly supports the view that the death toll in the Haiti earthquake was socially influenced
187 - the Haiti earthquake plots above the line indicating greater than expected vulnerability even for a
188 country with this extreme poverty - but it suggests that this influence is smaller than might commonly
189 be supposed. The anomalous vulnerability of Iran, equivalent to that of Haiti despite an order of
190 magnitude greater GDP, might be explained by the particular geographical challenges it faces in
191 imposing earthquake safe construction^{23,24}, but still identifies it as the most anomalously vulnerable
192 nation globally. The anomalous resilience of the Philippines, on the other hand, when compared to
193 countries like India and Guatemala, which, superficially at least, face similar geographic and
194 economic conditions, appears exemplary and is likely due, at least in part, to its development of an
195 integrated disaster management system²⁵ despite modest national income. Other contrasting pairs
196 include Chile and Turkey, and Peru and Guatemala. Also worthy of note is that, despite their
197 significantly higher wealth, Italians by this analysis are as vulnerable as Chinese, and Greeks are as
198 vulnerable as Indonesians. It is, of course, easy to speculate on explanations for these contrasts, and
199 some of them are likely to be unalterable; we believe, however, that given the importance of their
200 implications, they deserve more detailed investigation.

203 4. Conclusions

204 In conclusion, this analysis suggests that cost-neutral, social interventions have increased earthquake
205 resilience in some countries and, conversely, that their absence exposes other populations to
206 continuing high vulnerability. Perhaps more importantly, we believe that this type of analysis has the
207 potential to direct sociological or political, investigations which might ultimately provide a solid basis
208 for international cooperative learning. The sociological exploration of the origins of the contrasts
209 revealed above, for example, might more rigorously explain their underlying causes enabling the
210 identification and characterisation of evidence-based, low-cost interventions which in turn might
211 provide the political impetus for action.

212 There can never be any substitute for better building in reducing vulnerability to strong seismic
213 shaking, but until expensive engineering solutions become more universally available, dispassionate,
214 rigorous quantification of vulnerability must, we believe, be placed in the vanguard of providing a
215 scientific evidence-base to identify and disseminate affordable best-practice internationally. To date,
216 efforts at political persuasion towards improving earthquake resilience have focused on the
217 necessarily long-term and spatially-imprecise assessment of earthquake hazard but, in the absence of
218 recommendations for cost-neutral interventions, earthquake mortality has continued to increase
219 exponentially. Until we robustly quantify our assessment of earthquake resilience building, and can
220 endorse effective and affordable responses to this poorly-defined, high-impact, low-probability
221 threat, investment will likely remain a low priority across much of the developing world. While it
222 does, death tolls in earthquakes will continue to grow.

223 Appendix

224 A1. Additional Definitions

225 We begin with the definition of the shake potency s in (1), and choose the form $w_k = \alpha_k 10^{k-(K+1)}$ for
226 the weights. The mortality may be modelled using the relationship

$$\ln \lambda = a \ln s + b \quad (2)$$

where $\lambda(\mathbf{D}_i) = s_i^a(\mathbf{D}_i)e^b$ is the expected value for the number of deaths in the event, given the shaking intensity profile, $\mathbf{D}_i = [d_{i1}, \dots, d_{iK}]$.

A2. Choice of Error Model

We have assumed that, provided our model is well-specified with respect to the shaking, the component of the variance associated with this process will be stochastic and can be described by a Poisson-based distribution. However the data are clearly over-dispersed with respect to a simple Poisson model, which has variance $\sigma^2(\lambda) = \lambda$ and, although the stochastic part of this may be specifically Poisson over-dispersed, i.e. $\sigma^2(\lambda) = \phi\lambda$ where ϕ is a constant, we know that a significant part of the variance is due to systematic, and not stochastic, processes, chiefly the omission from the model of social factors. Without independent constraints on the magnitude of the stochastic component, we are unable to quantify the degree to which the mortality in any event is explained, or not explained, by our model, whether the magnitude of the total variance is assumed or is a free parameter in the model.

We expect the form of the error model to control both the parameter estimates and the distribution of data that results from the optimisation. However, an alternative has been tested, which assumes a Gaussian distribution of $\ln s$, where the mean is directly proportional to the mortality in the event and the standard deviation is a free parameter, which is independent of the mortality. This model could be expected to yield very significantly different results from a Poisson based optimisation. However, we find that, although the parameter estimates and distribution of data are altered, the systematic trends in social parameters, that are the subject of this paper, remain qualitatively unchanged. In particular, the trends identified in vulnerability (shown in figure 2 for truncated Poisson), persist even using the Gaussian error model.

Our decision to use the Poisson model is in an effort to model the expected structure, if not the magnitude, of the stochastic component of the errors. For the reasons given above, we have chosen not to attempt to model the Poisson over-dispersion parameter ϕ simultaneously. The aim is that, after optimisation, as much of the data as possible is explained by the shaking process with Poisson errors, before we begin to make inferences about where and why the model fails.

A3. The truncated Poisson distribution

Since data for events with less than 10 deaths recorded are omitted, we use a truncated form of the Poisson distribution. The number of deaths is represented by the random variable Y ; for truncation at $y = r$ the probability mass function is given by

$$f_r(y|\lambda) = \Pr(y|\lambda, y > r) = \frac{\Pr(y \cap y > r|\lambda)}{\Pr(y > r|\lambda)} = \begin{cases} 0 & y \leq r \\ \frac{f(y|\lambda)}{1 - F(r|\lambda)} & \text{otherwise} \end{cases}$$

where $f(y|\lambda) = \lambda^y e^{-\lambda}/y!$ is the probability mass function of the corresponding non-truncated distribution with mean λ and $F(r|\lambda) = \sum_{y=0}^r f(y|\lambda)$ is the cumulative mass function, evaluated at $y = r$. Defining

$$T_r(\lambda) = 1 - F(r|\lambda)$$

we can write the moment generating function as

$$M_Y(t) = \frac{1}{T_r(\lambda)} \left[e^{\lambda(e^t-1)} - \sum_{y=0}^r f(y|\lambda) e^{ty} \right]$$

allowing us to find the expected value, $E[Y] = \mu_r(\lambda)$, and variance, $\sigma_r^2(\lambda)$, used to calculate the expected value and intervals in Figure 1a for the optimised model (2). We find $T_9(\lambda) \rightarrow 1$, $\mu_9(\lambda) \rightarrow \lambda$ and $\sigma_9^2(\lambda) \rightarrow \lambda$ at $\lambda \gtrsim 20$ and estimate that for $\sim 6\%$ of the data with $y \geq 10$ the simple Poisson approximation is not valid.

270 A4. Maximum Likelihood Estimation

271 a and b are unconstrained, so the set of parameters for estimation is $\theta = \{a, b, \alpha_1, \dots, \alpha_K\}$. Since $\lambda_i =$
 272 $\lambda(\theta, \mathbf{D}_i)$ we write the log-likelihood function as

$$273 \quad \ell(\theta | \mathbf{Y}, \mathbf{D}) = \sum_{i=1}^N \ln f_r(y_i | \theta, \mathbf{D}_i)$$

274 where $\mathbf{Y} = [y_1, \dots, y_N]$ is the set of data for the number of deaths in each earthquake i and

$$275 \quad \ln f_r(y_i | \theta, \mathbf{D}_i) = y_i \ln \lambda_i - \lambda_i - \ln y_i! - \ln T_r(\lambda_i)$$

276 Maximising the likelihood therefore involves minimising the function

$$277 \quad g(\theta) = \sum_{i=1}^N [\lambda_i + \ln T_r(\lambda_i) - y_i \ln \lambda_i] \quad (3)$$

278 We use the gradient based BFGS optimisation algorithm²⁶. So that all α_k remains positive, we set
 279 $\alpha_k = 10^{\beta_k}$ and optimise with respect to β_k . We also require $2 + K$ 1st order partial derivatives of $g(\theta)$.

280 A5. Non-uniqueness of the solutions

281 In this formulation, solutions for $\{\hat{b}, \hat{\beta}\}$ are not unique. Taking $\alpha' = A\hat{\alpha}$ and $s(\alpha') = As(\hat{\alpha})$ so that we
 282 have uniform scaling of both $\mathbf{w}$ and s , we can see from (2) that $\lambda(\alpha') = \lambda(\hat{\alpha})$ if $b' = b - a \ln A$. From
 283 (3), therefore, $g(\hat{\alpha}, b', \alpha') = g(\hat{\alpha}, \hat{b}, \hat{\alpha}) \equiv \gamma$. Any uniform scaling of the optimised weights corresponds
 284 to another solution for the minimum, provided the value of b in (2) is adjusted accordingly.

285 We define a set of arbitrary reference values for the optimised weights, corresponding to α^* , which
 286 represent the relative values of the components of $\hat{\alpha}$. Defining A so that, for example, $\alpha_v^* = 1$ where
 287 v is to be chosen from $k = 1, \dots, K$, we have

$$288 \quad A = \hat{\alpha}_v = 10^{\hat{\beta}_v}$$

289 and

290 $b_{(v)}^* = \hat{a} \ln 10 \hat{\beta}_v + \hat{b}$

291 As a method for determining the value of b^* , we therefore systematically vary b , optimising all
 292 components of β . In this case, the relationship between $\hat{\beta}_v$ and $\hat{b}_{(v)}$ will be linear for all $v = k$, with
 293 gradient $c_v = c = 1/a \ln 10$ and intercept $d_v = b_{(v)}^*/a \ln 10$. This approach is preferable to, for
 294 example, setting $\beta_v = 0$ to find $b_{(v)}^*$ directly, as it provides a test that the components of β^* are robust
 295 with respect to changes in b .

296 A6. Optimisation Procedure

297 Based on the discussion above, the following procedure has been adopted:

- 298 1. Perform a coarse grid-search over $\{a, b\}$ at $\beta = 0$ to provide initial estimates. This is maximum
 299 likelihood line-fit to the data with $\beta = 0$.
- 300 2. Optimise β using the BFGS algorithm, with $\{a, b\}$ set according to the results of the grid-
 301 search, and the approximation to the inverse Hessian for β , $\mathbf{B}_{i=1}$, initialised to the identity
 302 matrix ($i = 1$ here refers to the 1st iteration).
- 303 3. Initialise $\mathbf{A}_{i=1}$, the approximation to the inverse Hessian for $\{a, b\}$, to the identity matrix.
- 304 4. Iterate:
 - 305 a. Optimise $\{a, b\}$ with β fixed
 - 306 b. Optimise β with $\{a, b\}$ fixed,
- 307 initialising $\mathbf{A}_i$ and $\mathbf{B}_i$, at iteration $i \geq 2$, to their *optimised* values at the previous iteration, $i -$
 308 1. The solution converges on an arbitrary $\hat{\theta} = \theta^1 = \{\hat{a}, b^1, \beta^1\}$, depending on the start values
 309 of the parameters and the relative size of the gradients. In general, without scaling the
 310 parameters, the solution is dominated by the start value of b , since $\partial g(\theta)/\partial \beta_l 10^{l-(K+1)}$.
- 311 5. Fix $\hat{a}$ according to the results of Step 3. Vary b systematically and re-optimize β for each b .

6. Perform a line fit for β_v vs b for all $v = k$. Calculate b^* and $\theta^* = \{a, b^*, \alpha^* = 10^{\beta^1 - \beta_v^1}\}$, where β_v^1 is the v^{th} element of β^1 and v has been chosen according to the standard errors in the line fits.

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Figure Legends

Fig. 1 Shake Potency plotted against the number of deaths attributed to strong shaking in fatal earthquakes. Colours of all symbols indicate the GDP. The red and green (truncated at $r=10$) lines show the model as in equation (2); the black lines show the structure of the Poisson uncertainties that have been used to optimise the model (according to the procedure outlined in the Appendix). A) All

386 earthquakes with more than 10 fatalities. B) s - y space almost completely discriminates between
387 earthquakes occurring in Iran (stars) and the Philippines (circled points). USA (red points) and Japan
388 (orange points) are included for context.

389 **Fig. 2.** Shaking vulnerability. EVI as a function of log GDP for countries experiencing three or more
390 earthquakes which killed more than 10 people. The best fit to the data has been estimated by using a
391 weighted least squares method. We compare the simplest (linear) model, where we fix the gradient
392 at -1, with a model in which the gradient is a free parameter, using the standard Akaike information
393 criterion (which penalises overfitting). We find that the fixed gradient model is the more parsimonious
394 fit and this is presented, though our argument is unchanged using either, since both divide the data
395 into two roughly equal groups. Neither Haiti nor New Zealand appear in the chart since neither had
396 three or more deadly earthquakes in the data we examined, but for illustration we show the location
397 for the Haiti (H) earthquake and show the two deadly New Zealand (NZ) tremors as hollow symbols.
398 This plot certainly supports the view that the difference in death toll in the Haiti and Darfield events
399 was socially influenced, but suggests strongly that this influence is much smaller than is widely
400 believed.

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