USING EXPERT JUDGMENT TO ASSESS ADAPTIVE CAPACITY TO CLIMATE CHANGE: EVIDENCE FROM A CONJOINT CHOICE SURVEY[1]

By

Anna Alberini
AREC, University of Maryland
and Fondazione Eni Enrico Mattei
aalberini@arec.umd.edu

Aline Chiabai
Fondazione Eni Enrico Mattei
aline.chiabai@feem.it

And

Lucija Muehlenbachs
AREC, University of Maryland
lmuehlenbachs@arec.umd.edu

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Address for Correspondence:

Anna Alberini
AREC, 2200 Symons Hall
University of Maryland
College Park, MD 20742

e-mail: aalberini@arec.umd.edu
phone: 001 301 405-1267
fax: 001 301 314-9091

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Abstract

We use conjoint choice questions to ask a sample of public health and climate change experts contacted at professional meetings in 2003 and 2004 (n=100) which of two hypothetical countries, A or B, they deem to have the higher adaptive capacity to certain effects of climate change on human health. These hypothetical countries are described by a vector of seven attributes, including per capita income, inequality in the distribution of income, measures of the health status of the population, the health care system, and access to information.

Probit models indicate that our respondents regard per capita income, inequality in the distribution of income, universal health care coverage, and high access to information as important determinants of adaptive capacity. A universal-coverage health care system and a high level of access to information are judged to be equivalent to $12,000-$14,000 in per capita income.

We use the estimated coefficients and country socio-demographics to construct an index of adaptive capacity for several countries. In panel-data regressions, this index is a good predictor of mortality in climatic disasters, even after controlling for other determinants of sensitivity and exposure, and for per capita income. We conclude that our conjoint choice questions provide a novel and promising approach to eliciting expert judgments in the climate change arena.

JEL Classification: Q54 (Climate; Natural Disasters), I18 (Government Policy; Regulation; Public Health).

Keywords: Adaptive capacity, climate change, human health effects, extreme events, heat waves, vector-borne illnesses, conjoint choice, vulnerability, sensitivity.

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I. Introduction and Motivation.

The issue of adaptation to climate change and to its effects on human health and economic activities has received considerable attention among researchers and in policy circles as of late (Intergovernmental Panel on Climate Change [IPCC], 2001). Adaptation policies may be adopted in addition to seeking greenhouse gases emissions reductions, and whether or not a country or region is assumed to engage in adaptation has been shown to affect considerably the predicted damages of carbon emissions (Tol, 2005).[2] For example, agronomic approaches to the estimation of the effects of climate change on agricultural outputs and practices have been criticized on the grounds that they do not allow for adaptation (Mendelsohn et al., 1994, 1996; Polsky, 2004) and hence understate the benefits of the latter.

Klein (1998, 2003) presents a taxonomy of adaptation, distinguishing for proactive and reactive adaptation (depending on the time when the adaptation takes place), and private and public adaptation. Grothmann and Patt (2005) propose a model of adaptation that begins with an appraisal of the risk (where the probability of an adverse event is assessed, along with the potential extent of the damage caused by this event), and continues with an appraisal of possible options for adaptation, along with their costs.

One key question is whether it is possible to identify the characteristics of systems, such as communities or regions, that influence their propensity or ability to

[2] Yohe and Schlesinger (2002) note that some studies have been criticized for overstating the power of adaptation in reducing climate-related costs, especially when the adaptive capacity of developing countries

adapt (or their priorities for adaptation measures). Adaptive capacity is defined as the "potential, capability, or ability of a system to adapt to climate change stimuli or their effects of impacts" (IPCC, 2001), implying that in principle adaptive capacity has the potential to reduce the damages of climate change, or to increase its benefits. In other words, adaptive capacity affects a system's vulnerability to the stresses of climate change, along with the system's sensitivity and exposure.

Presumably, adaptive capacity varies widely, and assessment of adaptive capacity depends crucially on the time and geographical scale of reference. There may be considerable heterogeneity in adaptive capacity within a system. O'Brien et al. (2004) find that even in countries for which climate change is expected to be beneficial and/or that are thought to have a high degree of adaptive capacity (e.g., Norway), it is sometimes possible to identify regions and localities with much higher social and economic vulnerability to climate change. Grothmann and Patt (2005) emphasize that a community or system's *perceived* adaptive capacity may well be different from its *objective* adaptive capacity.

The IPCC (2001) identifies eight broad classes of determinants of adaptive capacity, namely (i) available technological options, (ii) resources, (iii) the structure of critical institution and decision making authorities, (iv) the stock of human capital, (v) the stock of social capital including the definition of property rights, (vi) the system's access to risk-spreading processes, (vii) information management and the credibility of information supplied by decision makers, and (viii) the public's perceptions of risks and exposure.

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was applied to the developing world. They also note that the amount of resources used up to reduce such costs is greatly affected by stochastic events and uncertainty.

To date, however, it has been difficult to empirically measure it and establish the relative importance of the factors identified by the IPCC.[3] Although most observers believe that income is a key factor in determining adaptive capacity, others have argued that what matters are the channels through which resources influence adaptive capacity (e.g., access to information, Phillips, 2003) while others have raised doubts about the importance of resources alone (Patt and Gwata, 2002). Pelling and High (2005) emphasize the need for incorporating social capital in the discussion about adaptive capacity.

In spite of these difficulties, many researchers agree that it would be useful to produce indicators/indices of adaptive capacity for the purpose of understanding its determinants and prioritizing interventions (Adger and Vincent, 2005; Haddad, 2005). Much uncertainty, however, still surrounds the factors that shape adaptive capacity and how their future evolution can be predicted (Adger and Vincent, 2005). An additional hurdle to the development and use of indicators of adaptive capacity is that their construct validity must be demonstrated. In other words, it is important to show that an indicator or index is truly measuring what it purports to do.

Indices of adaptive capacity have been based on expert judgments and/or expert judgments combined with measures of the degree of economic development of a country, or region, plus socio-demographic and institutional characteristics (e.g., Brooks et al., 2005). In the latter case, considerable effort has been devoted to examining the stability of indices and indicators with respect to the construction of weights used to aggregate these measures.

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[3] See Yohe and Schlesinger (2002) and Brooks et al. (2005) for a discussion of the time scale over which events and adaptation take place.

In this paper, we propose a novel approach for identifying the role of factors generally linked with adaptive capacity with respect to selected categories of human health effects of climate change (those associated with (i) extreme weather events, (ii) thermal stresses, and (iii) vector-borne illnesses). The goal of our paper is four-fold. First, we wish to infer what factors are judged by experts to be the most important determinants of adaptive capacity with respect to the abovementioned types of human health effects.

Second, we wish to find out how experts trade off such factors against each other in assessing a country's adaptive capacity. For example, when it comes to adaptive capacity, can a more egalitarian distribution of income make up for a lower income per capita? Or, how much wealthier does a country need to be to make up for the absence of a universal health care system?

Third, we use the experts' judgments to compute a simple index of adaptive capacity. We use this index—and this is the fourth goal of our study—as one of the independent variables in a regression relating vulnerability, which we measure as deaths per million in extreme weather events, to proxies for sensitivity, exposure, and adaptive capacity.

We accomplish these goals by surveying a total of 100 public health experts, climatologists, and emergency response officials intercepted at professional conferences and intergovernmental meetings using a structured questionnaire. Our survey questionnaire relies on conjoint choice questions.[4] Given two stylized (and hypothetical)

[4] In a typical conjoint choice exercise (Louviere et al., 2000), respondents are presented with a set of K hypothetical alternatives (the so-called "choice set," where K≥2) representing situations, goods or public policies. The alternatives are described by a vector of attributes, and differ from one another in the level of two or more attributes. Respondents are asked to indicate which of the K alternatives they deem the most attractive, K being at least two. It is assumed that in choosing the most preferred alternative, the respondent chooses the one that gives him the highest utility (here, the highest adaptive capacity) and that

countries, which we describe in terms of resources and distribution of resources, population health and age, health care systems, and access to technology and information, we ask which, in the respondent's opinion, has the higher adaptive capacity.

The responses to these choice questions allow us to identify the factors that experts associate with a higher or lower degree of adaptive capacity to (i)-(iii), and the tradeoffs experts make between different factors. The statistical analysis of the responses to the choice questions relies on a random adaptive capacity framework and on a variant of the probit model. We use the probit coefficients to produce our index of adaptive capacity. Within Europe and Central Asia, the index is low for transition economies and the former Soviet Republics, and high for Western European countries. Even the poorest countries in Europe and Central Asia, however, are well ahead of countries in Asia and Africa.

As a final check on the quality of the adaptive capacity index, we run a regression relating deaths in climatic disasters in a country in a year (normalized by population) to determinants of exposure and sensitivity *and* to our index. Based on panel data from over 140 countries over 1990-2003, we find that the adaptive capacity index is negatively correlated with deaths, and that it accounts for a relatively large share of the explanatory power of the regression, even controlling for the country's GDP per capita.

Our approach and that by Brooks et al. (2005) are nicely complementary. Brooks et al. first develop a list of 46 factors thought to be associated with vulnerability, and compute pairwise correlations between country-level proxies for the former and mortality

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he trades off the attributes of the alternatives. The conjoint choice approach has previously been used to attach a monetary value to private goods, environmental goods or natural resource management plans (e.g., Adamowicz et al., 1994; Boxall et al., 1996; Hanley et al., 2001), and other public policies (Alberini et al., 2005), and hence to estimate their monetized benefits.

rates in extreme weather events for each of the last three decades of the twentieth century. They then pare down the original list to 11 indicators (those for which the pairwise correlation is significant at the 10% level or better), and form a summary vulnerability index measure based on the quintile a country falls in for each indicator. Since this summary index assumes an equal weight for each of the 11 indicators, Brooks et al. use the indicator rankings provided by a panel of seven experts to assess the sensitivity of the vulnerability index to changing the weights.

Clearly, the primary focus of Brooks et al. is on vulnerability, although they recognize that vulnerability depends crucially on adaptive capacity. Another difference between their work and ours is the role played by expert judgments: It is the starting point of our research (we elicit expert opinions, form an index based on them and check it against actual mortality figures in multiple regressions), whereas it is used for sensitivity analysis purposes in theirs. Since our adaptive capacity index is formed directly from the experts' responses to the choice questions, it implicitly subsumes the weights that they assign to the various country attributes.

II. Formal Models and Measures of Adaptive Capacity

Building on the conclusions of the IPCC report, Yohe and Tol (2002) propose a formal model where vulnerability (i.e., the losses caused by climate change) is a function of exposure and sensitivity,[5] which in turn depend on adaptive capacity. Formally,

(1) $$\mathbf{V} = \mathbf{V}(\mathbf{E}(A), \mathbf{S}(A)),$$

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[5] Vulnerability describes the extent to which a system is susceptible to sustaining damage from climate change (IPCC, 2001). Exposure is the degree of climate stress upon a particular unit of analysis, and sensitivity is the degree to which a system will respond to a change in climate (IPCC, 2001).

where **V** is a vector of variables that capture vulnerability, **E** is a vector that measures exposure and **S** is sensitivity. *A* is adaptive capacity, which is expressed as a scalar and is a function of the economics, social and legal determinants D_j identified in IPCC (2001):

(2) $$A = A(D_1, D_2, ..., D_m),$$

where j=1, 2, …,m. Yohe and Tol argue that it is reasonable to expect vulnerability to increase at an increasing rate with exposure and sensitivity, and that the latter should decrease at a decreasing rate with adaptive capacity *A*. The multivariate functions (1) and (2) are time- and location-specific, implying that vulnerability and adaptation at one place and time may or may not be the same at a different place and time.

Yohe and Tol use data from several countries to estimate an empirical model of vulnerability to extreme events. Their regression models relate three alternate measures of vulnerability (fraction of population affected by disaster events, damages, and number of deaths) to the country's per capita income, Gini coefficient, and population density. These vulnerability measures are generally negatively related to income, and—depending on the equation—positively related to inequality and population density.

Yohe and Tol's model confirms the expected relationship between resources and vulnerability, but its stylized nature does not allow one to disentangle by how much adaptive capacity mitigates exposure and sensitivity. For each adaptive capacity variable, Yohe and Tol propose an index of coping capacity, which is the product of efficacy and feasibility, and is specific for each project or adaptation policy under consideration.

Luers et al. (2003) propose to measure adaptive capacity as the reduction in vulnerability that could be potentially attained at new conditions. Formally, they first define vulnerability V as the change in the well-being W of a community as variable X is changed, divided by the percentage increase in W over the baseline W_0 (or threshold until which no damage is experienced):

(3) $$V = \frac{\partial W / \partial X}{W / W_0}.$$

Adaptive capacity is thus V at the present condition minus V at the modified condition.[6] They apply these indicators to farmers in the Yaqui Valley in Mexico, using wheat yield as their measure of well-being and emphasizing the role of soils and soil management in determining vulnerability and adaptive capacity.[7]

National-level assessments have been judged as useful for understanding factors that undermine or improve resilience to climate stresses, and for prioritizing adaptation interventions and foreign aid (Adger and Vincent, 2005). Haddad (2005) rates countries' adaptive capacities conditional on national aspirations to (i) maximize the sum of individual utilities, (ii) achieving contractarian liberalism, (iii) achieving or maintaining dictatorship or theocracy, and (iv) achieving or maintaining technocratic governance. He constructs scores as the weighted sum of three economic criteria, three indicators of civil freedom, one measure of inequality in the distribution of income (the Gini index) plus two indicators capturing the availability and politics of a key natural resource—water. The weights depend on the regime for which the assessment is made.

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[6] If different units face different exposure, one must take the expectation of V with respect to the density of X. The definition of adaptive capacity is thus amended by replacing this mean vulnerability in lieu of equation (3).

[7] Luers et al.'s approach differs from other indicators and indices of vulnerability in that it focuses on one or few variables of concern and specific sets of stressors, rather than attempting to quantify the vulnerability of a place. The latter approach is used, for example, in indicators of vulnerability to food insecurity (US AID Famine Early Warning System, see www.fews.org/fewspub.html), and in country-level assessments, such as the Environmental Vulnerability Index (Kaly et al., 2002), the index developed by the Vulnerability Assessment Program (Moss et al., 2002), and the Social Vulnerability Index (Adger and Vincent, 2005).

The model gives ordinal rankings of nations in terms of their adaptive capacity to climate change in pursuit of their national aspirations, and can be used to prioritize foreign aid. As one would expect, Haddad shows that when the goal is to maximize the sum of individual utilities, the US, Australia, New Zealand, and Western Europe countries are in the top quintile, but the US would be only in the second quintile when the goal is to attain contractarian liberalism, due to the importance that such a goal places on equality in the distribution of income.

III. Structure of the questionnaire and sampling frame.

A. Structure of the Questionnaire

Our questionnaire (reported in Appendix A) is divided into 5 sections. Section A provides a brief description of global climate change and its effects. Respondents are told that climate change may have numerous effects on human health, but that in this survey we would like them to focus on three, namely (i) deaths and injuries associated with floods and landslides caused by sustained rains or extreme weather events, (ii) cardiovascular or respiratory illnesses and deaths during heat waves, and (iii) vector-borne infectious diseases.[8]

In section B, we ask respondents how important (i), (ii) and (iii) are to the respondent's organization and to the respondent himself (or herself). We then briefly introduce the concept of adaptive capacity, explaining that country and local governments may in some cases implement adaptation policies to reduce (i)-(iii).

[8] Other possible effects of climate change on human health include psychosocial effects, hunger and malnutrition due to famine and drought, food borne and waterborne illnesses, etc. We recognize that these effects may be potentially severe, but they are disregarded within the context of our survey questionnaire.

Section C contains the conjoint choice questions. Respondents are explicitly told that they will be asked to consider pairs of hypothetical countries that could be located anywhere in the world. Based on the countries' description, the respondent must indicate which of the two countries in a pair he believes to have the higher adaptive capacity.

Respondents face a total of four choice questions. The first two refer to countries with relatively high population densities (400 people per square kilometer), a mild climate, significant amounts of coastline and mountains, a relatively high degree of deforestation, and are moderately subject to floods and landslides. The last two choice questions refer to pairs of countries with a cold climate, relatively low population density, little deforestation, significant amounts of coastline and mountains, and little experience with extreme weather events in the past. We wish to emphasize that the countries are described solely by the levels of their attributes and the high/low exposure scenarios, and are not labelled or identified in any other way. We believe that our decision to show respondents stylized and nameless "countries" has two important advantages. First, the respondents should be free from prejudice about specific nations. The second advantage is of a statistical nature: This approach allows us to control for the level of similarity across the "countries" to be compared, and to show respondents combinations of attributes that are relatively rarely found in real life, which makes it easier to disentangle the incremental effect that changing one attribute will have on adaptive capacity.[9]

The cCASHh project focused primarily on Europe, where these costs are likely to be small or cannot be measured or predicted reliably.

[9] To further elaborate on this point, suppose a respondent was asked to compare a hypothetical country with income, level of inequality, etc. similar to those of the US with a hypothetical country where income, inequality, etc. are similar to those of a nation in Sub-Saharan Africa. We would expect virtually all respondents to tell us that the former country is the one with the higher adaptive capacity. Our approach, however, implicitly allows us to ask respondents to focus on the following question: What happens to adaptive capacity if I take the former country (the one that for income and other attribute levels resembles

Section D asks questions about the professional background of the respondents, and section E concludes with debriefing questions that inquire about the clarity of the questions and of the choice exercises.

B. The Choice Questions

While researchers have discussed the potential role of many social, economic, and institutional factors in determining a community's adaptive capacity to climate change, we rely on a relatively small number of attributes in our conjoint choice tasks due to sample size considerations and to limit the cognitive burden imposed on the respondent.

Our stylized, hypothetical countries are defined by a total of 7 attributes: (i) per capita income (in US dollars), (ii) a qualitative description of the level of inequality in the distribution of income ("high" or "low"), (iii) the proportion of the country's population of age 65 and older, (iv) life expectancy at birth, (v) physicians per 100,000 residents, (vi) the type of health care system (universal coverage, or based on private health insurance), and (vii) access to information via television, radio, newspaper, and internet ("high" or "low"). These attributes may capture both macro/national and micro/local factors discussed in Yohe and Tol (2002).

We arrived at this set of attributes after reviewing the literature, consulting with public health and climate change researchers, and developing a first list of candidate descriptors, which was pared down after pre-testing earlier versions of the questionnaire at the World Health Organization (WHO) meetings and at the Climate Change and Adaptation Strategies for Human Health in Europe (cCASHh) project coordination

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the US) and assign it the same income as a Sub-Saharan African nation? Would such a country have higher or lower adaptive capacity than a Sub-Saharan African if the latter had with high access to information?

meetings held in Freiburg in May 2003, in Prague in June 2003 and in Potsdam in July 2003. Our final list of attributes is broadly consistent with those used by Haddad (2005), Adger and Vincent (2005) and Grothmann and Patt (2005).[10]

Our experimental design (summarized in table 1) uses three possible levels of income per capita: 13,000, 20,000 and 27,000 US dollars. These were selected because the original goal of the research project was to study adaptive capacity in Europe, and these figures are close to the per capita incomes of countries that have recently joined the European Union, such as the Czech Republic (13,991 US dollars), and of certain European Union countries. For example, in 2000 Spain's per capita income was 19,472 US dollars, Italy's was 23,626 US dollars and Belgium's was 27,178 US dollars.

Table 1—Attributes and attribute levels in the conjoint choice questions

Attribute	**Levels of the attribute**
Per capita income (US dollars)	13000, 20000, 27000
Inequality in the distribution of income	Low, high
Percentage of population older than 65 years	12%, 18%
Life expectancy at birth	70, 79
Physicians per 100,000	250,300,400
Health care system coverage	private, universal
Access to information via newspaper, television, radio, internet	low, high

We use two possible levels for the percentage of the elderly in the population: 12%, which corresponds to a relatively "young" country (such as Ireland), and 18%,

[10] For comparison, Brooks et al. (2005) wished to produce an index of vulnerability, and developed a first list that was comprised of 46 possible indicators of vulnerability. Only those indicators that were significantly correlated with decadal mortality rates in extreme events were included in the final list, which was comprised of 11 indicators and was shown to a panel of experts. We were somewhat less structured in our selection approach, which was based on discussions with the individual experts and on the comments that they provided on early drafts of the questionnaire. We faced severe sample size constraints that dictated that the final list of attributes be as succinct as possible. We also felt that a relatively simple list

which corresponds to a relatively "old" country (e.g., Italy) in 2000. The WHO statistics on the number of physicians per 100,000, which is a measure of access to health care widely used in public health, suggest that there is much variability across countries in this index.[11] In the end, we selected three possible levels: 250, 300 and 400 physicians per 100,000.

For life expectancy, we focus on 70 and 79 years. The former is life expectancy at birth in Eastern European countries such as Romania and Bulgaria, while the latter is the approximate figure for Italy, France and Sweden, among other Western European countries. The remaining three attributes (health care system, inequality in the distribution of income, and access to information) are of a qualitative nature.

In our conjoint choice questions, each choice set consists of two artificially created, hypothetical countries. To form these pairs, we first created the full factorial design, i.e., all possible combinations of the levels of the attributes.[12] Next, we randomly selected two country profiles, but discarded pairs containing dominated alternatives.[13] This was repeated for a total of four conjoint choice questions per respondent, making sure that each set of four pairs did not contain duplicate pairs. We created 32 different

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was appropriate for our main survey administration mode, which entailed contacting experts at professional conferences and asking them to complete the questionnaire on the premises, if possible.

[11] For example, there are 164 physicians per 100,000 in the UK, 345 in Bulgaria, and 554 in Italy.

[12] This is comprised of $2^5 \times 3^2 = 32 \times 9 = 288$ possible combinations.

[13] An alternative in a pair is dominated if it is obviously worse than the other. In deciding whether there is a dominating alternative, we reasoned that countries with higher income should be judged to have higher adaptive capacity, and so should countries with lower inequality in the distribution of income, longer life expectancy, more numerous physicians per capita, and better access to information. Clearly, pairs of countries that contain only non-dominated alternatives result in a non-orthogonal design. In our view, showing respondents only pairs with non-dominated alternatives is essential for the credibility of the survey. We used simulations (GAUSS program available from the authors) to check the properties of one such design, and found that, as long as there is sufficient variation in the levels of the attributes in the resulting pairs, the non-dominated design performs well, in the sense that (i) the estimates of the coefficients of the model in section V are virtually unbiased, and (ii) there is only a very small loss of statistical efficiency for such estimates relative to the full design.

versions of the questionnaire following this approach. Respondents were randomly assigned to a questionnaire version.

The first two conjoint choice questions refer to countries A and B, and C and D, respectively, which are portrayed as enjoying a mild climate, but a relatively high propensity to extreme events, and high deforestation. The countries in the remaining two pairs (E and F, and G and H, respectively) have colder climates, are relatively unlikely to experience extreme events, and have had little deforestation.

C. Sampling frame and Survey Administration

Our questionnaire was self-administered by a sample of public health officials and climate change experts intercepted at random at professional conferences and intergovernmental meetings from October 2003 to August 2004.[14] This was a pen-and-paper questionnaire, so study participants were offered the option to fill out the questionnaire on the premises, or to return it by fax or mail. Everyone we contacted in this fashion completed the questionnaire, for 70 questionnaires.

We supplemented this sample by mailing the questionnaire to 100 experts selected among the attendees of other professional conferences on climate change and public health, or that had participated in various capacities in other research projects about climate change and public health. The mailings resulted in an additional 30 questionnaires, for a total sample size of 100 completed questionnaires.

[14] These conferences include the 2003 International Healthy Cities Conference, Belfast, Northern Ireland, 19-22 October 2003; the World Climate Change Conference, Moscow, 29 September-3 October 2003; the 2003 IPCC Conference, Orlando, Florida, 21-24 September 2003. Additional participants were recruited

IV. The Survey Data

We cannot make any claims that our sample is representative of the population of these professions, so our first order of business is to describe the individual characteristics of our respondents. Males account for over two-thirds (67.35%) of our sample, and the age ranges from 24 to 70 years, for an average of 48. Our respondents were from a total of 29 countries (67% from Western Europe, 15% from former Eastern bloc countries, 5% from the United States, with the remainder coming from Thailand, Turkey, Brazil, Japan, Congo, Israel and Nigeria).

Table 2 reports information about the experts' professional backgrounds, showing that medical, public health/epidemiology, engineering, and economics/business fields accounts for about two-thirds of the sample.

Table 2 – Professional background of the respondents.

	Percentage (frequency)
Medical	19.15% (18)
Public health or epidemiology	15.96% (15)
Engineering	12.77% (12)
Economics or business administration	19.15% (18)
Other	32.98% (31)

In table 3, we show the composition of our sample by type of organization. Public health organizations are well represented in our sample (22.4% of the respondents), as are Universities or other research institutions, which account for 38% percent of the sample. About 19% of our respondents work for government agencies,

among the participants of the MIT Global Climate Change Forum XXI, Cambridge, Massachusetts, 8-10 and the remainder of the sample is comprised of persons who work for health care organizations (both public and private), emergency response agencies, and other organizations.

Table 3 – Type of organization where the respondent works.

Type of organization	Percentage of the sample
1. Public health organization	22.4
2. Private or public health care organization	7.5
3. Emergency response agency	2.1
4. University or research institution	38.3
5. Another government organization	19.2
6. Non-government, non-profit organization	2.1
7. Private company	4.2
8. Another type of organization	4.2

Table 4 displays the frequencies of the responses about concern for the effects of climate change on human health within the respondent's organization. Table 5 reports the respondents' professional concern about these issues.

Table 4 – Organization concern about the effects of climate change. Percentage selecting each response category.

	Very concerned	Somewhat concerned	Not concerned at all	No position/ outside the organization's mission
1. Deaths and injuries due to floods, landslides and mudslides	31.00%	45.00%	10.00%	14.00%
2. Cardiovascular and respiratory illnesses due to heat waves	43.00%	34.00%	12.00%	11.00%
3. Increased cases of vector-borne diseases	34.00%	35.00%	17.00%	14.00%

October 2003.

Table 5 – Respondent professional concern about the effects of climate change. Percent selecting each response category.

	Very concerned	Somewhat concerned	Not concerned at all	No position/ outside of professional duties
1. Deaths and injuries due to floods, landslides and mudslides	27.55%	37.76%	12.24%	22.45%
2. Cardiovascular and respiratory illnesses due to heat waves	33.67%	36.73%	7.14%	22.45%
3. Increased cases of vector-borne diseases	30.61%	32.65%	9.18%	27.55%

These tables show that roughly one-third or more of the respondents stated that their organization was highly concerned about the three classes of effects of climate change covered in the survey. Similar percentages selected the highest category of professional concern for these effects.

Regarding the choice questions, the responses were well balanced, in the sense that our experts chose the first of the two countries in a pair (e.g., A between A and B) 45.60% of the times, and the second country of the pair 54.40% of the times. This is a nice split that suggests that there were no obvious choices, and that people did indeed trade off attributes.[15]

In debriefing questions at the end of the questionnaire, about 66% of the respondents stated that they took into account all of the three major effects of climate change on human health when answering the choice questions, as we instructed them to

[15] Further inspection of our data reveals that most of our study participants (92%) found the description of the consequences of climate change adequate, and that only 15.5% noted that the information on climate change provided in the questionnaire was new to them. Roughly 89% of the respondents found the concept

do. Almost 19% of the sample said that they had thought exclusively about extreme weather events, and 5.3% told us that they had considered only thermal stresses. Vector-borne diseases were cited as the only reason for the responses to the choice question by 2.1% of our sample, and, finally, 7.4% said that their choice responses were motivated by other effects of climate change.

V. The Model.

This section provides a theoretical model to motivate our statistical analysis of the responses to the choice questions. We assume that when answering the conjoint choice questions, individuals select the alternative with the higher level of adaptive capacity out of the two in the choice set. We further assume that the level of adaptive capacity of a country, A^*, is an unobservable random variable, and that the adaptive capacity level that expert i associates with alternative j, A_{ij}^*, is comprised of two components: a deterministic component, which is a linear function of the attributes of the alternative via a vector of unknown, fixed coefficients, β, and a stochastic error term. Formally,

(4) $$A_{ij}^* = \overline{A}_{ij} + \varepsilon_{ij} ,$$

where $\overline{A}_{ij} = \mathbf{x}_{ij}\beta$, $\mathbf{x}_{ij}$ is the 1×p vector of attributes describing alternative j (j=1, 2) to individual i, β is a p×1 vector of coefficients, and ε is the error term. The error term captures individual- and alternative-specific factors that affect the choice and are known to the respondents, but not to the researcher. The vector **x** is comprised of continuous variables for income, physicians per capita, and life expectancy, and 0/1 dummy

of adaptive capacity clearly explained, and a similar fraction of the sample (88%) found the text and table presentation of the hypothetical countries clear.

indicators for high/low inequality in the distribution of income, universal coverage, and access to information. In the Grothmann and Patt (2005) framework, A_{ij}^{*} might be interpreted as expert i's view of the objective adaptive capacity of country j.

A_{ij}^{*} remains unobserved. What we *do* observe is which alternative is indicated by the respondent to have the higher adaptive capacity. Selecting, say, alternative 1 means that country 1 is deemed to have a greater adaptive capacity that country B. Since we observe a discrete choice out of two possible alternatives, the appropriate statistical model is a binomial model that describes the probability that the respondent selects option 1 between alternatives 1 and 2 in the choice set. Selecting country 1 means that A_{i1}^{*} is greater than A_{i2}^{*}:

(5) $$\Pr(1) = \Pr(A_{i1}^{*} > A_{i2}^{*}),$$

which in turn implies that the probability of choosing country 1 is

(6) $$\Pr(1) = \Pr\big((\varepsilon_{i2} - \varepsilon_{i1}) < (\overline{A}_{i1} - \overline{A}_{i2})\big) =$$
$$= \Pr\big(\eta_i < (\mathbf{x}_{i1} - \mathbf{x}_{i2})\boldsymbol{\beta}\big),$$

where $\eta_i = \varepsilon_{i2} - \varepsilon_{i1}$. If we assume that η_i is normally distributed with mean zero and variance 1, probability (6) is equal to:

(7) $$\Pr(1) = \Phi\big(\eta_i < (\mathbf{x}_{i1} - \mathbf{x}_{i2})\boldsymbol{\beta}\big),$$

where $\Phi(\cdot)$ is the standard normal cdf. Equation (7) is, therefore, the contribution to the likelihood in a probit model where the dependent variable is a dummy indicator taking on a value of one if the respondent chooses country 1, and zero otherwise. The independent variables of the probit equation are the differences in the level of the attributes between country 1 and 2, i.e., $(\mathbf{x}_{i1} - \mathbf{x}_{i2})$.

Probit equation (7) may be amended to include variables capturing individual characteristics of the respondent, which means that the probability of picking country 1 over country 2 is

(8) $$\Pr(1) = \Phi((\mathbf{x}_{i1} - \mathbf{x}_{i2})\boldsymbol{\beta} + \mathbf{z}_i\boldsymbol{\gamma}).$$

It is also possible to include interaction terms between the individual characteristics of the respondents and $(\mathbf{x}_{i1} - \mathbf{x}_{i2})$ to allow the same attribute to appeal to a different extent to different individuals. (An alternative approach that allows for heterogeneous preferences, the random-coefficient logit model, is described in Appendix B.)

Finally, since respondents engage in a total of four choice tasks, it is necessary to spell out our assumptions about the possible correlation between the errors η_{im}, where m denotes the choice task (m=1, .., 4), within the same individual. The simplest model treats these errors as mutually independent, so that the log likelihood function of the data is:

(9) $$\sum_{i}\sum_{m=1}^{4}\sum_{j=1}^{2} I_{ijm} \cdot \log \Pr(j \text{ in task } m).$$

Alternatively, a random-effects probit (see Greene, 2003) can be specified to account for the presence of unobserved heterogeneity, i.e., unobserved factors that influence choice and are common to all of the responses contributed by the same individual. The random-effects probit assumes that $\eta_{im} = \nu_i + \xi_{im}$, where ν_i is the individual-specific effect, which remains unchanged over all of the error terms of the same respondent (but varies across individuals), while ξ_{im} is a completely random error term. Both are assumed to be normally distributed, have mean zero, and be independent of one another. These assumptions imply that the pairwise correlation between any two η_{im} within individual *i* is the same.

Once the β coefficients are estimated by the method of maximum likelihood, we check their statistical significance using asymptotic t tests (for individual coefficients) and likelihood ratio tests (for subsets of the vector of coefficients). This allows us to tell whether the socio-economic variables we have used to describe adaptive capacity to our respondents *are* truly judged by them to determine adaptive capacity. The magnitude of the coefficient can be judged by examining the impact of changing attribute *k* on the probability of choosing country *j*.

Finally, we compute the rate of substitution between any two attributes. For example, if we wish to know what increase in GDP per capita is necessary to offset a small reduction in life expectancy at birth to keep adaptive capacity the same, we compute the ratio between their respective estimated β coefficients.[16]

Implicit in equation (9) is the assumption that the coefficients of the attributes are the same for the first two and the last two pairs of countries. Our first order of business is, therefore, to test the null hypothesis that the coefficients that apply in both pairs of countries are equal. If the null hypothesis is not rejected, it is acceptable to pool the responses to all of the conjoint choice questions.

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[16] To arrive at this result, we take the total differential of the systematic component of adaptive capacity, $\overline{A}_{ij} = \mathbf{x}_i\boldsymbol{\beta}$, with respect to the two attributes of interest, income and life expectancy, and set this differential to zero to hold adaptive capacity the same. This yields $dLIFEEXP \cdot \beta_{LIFEEXP} + dGDP \cdot \beta_{GDP} = 0$, and hence $\frac{dGDP}{dLIFEEXP} = -\frac{\beta_{LIFEEXP}}{\beta_{GDP}}$, which is the rate of substitution between the two attributes, assuming infinitesimal changes in income and life expectancy. The change in income that offsets a finite change in

VI. Conjoint Choice Responses: Model Results.

In this section we report the results of several variants on probit model (9). We first check whether people's β coefficients were different across the first two and the second two pairs of countries (first two and last two conjoint choice questions). We remind the reader that the first two pairs of countries share high population density, mild climate, extensive coastline and mountains, high deforestation, and moderate experience with extreme weather events. The second two pairs of countries differ from the first two in that they have low population density, colder climates, little deforestation, and little experience with extreme weather events. They should thus reasonably be expected to have different exposures to the most damaging consequences of climate change.

To test for structural change, we do a likelihood ratio (LR) test based on a relatively parsimonious specification of the probit equation that includes (the differences in) country attributes, but no individual characteristics of the respondents or interaction terms.[17] The LR ratio statistic is equal to 6.16, for a p-value of 0.62, failing to reject the null of no structural change at the conventional levels (i.e., 10%, 5%, and 1% significance).

This has two important implications. The first is that the experts view adaptive capacity as independent of exposure or risk of climatic disasters. The second is of a

life expectancy (e.g., one year) while keeping adaptive capacity the same is thus $\Delta GDP = -\frac{\beta_{LIFEEXP}}{\beta_{GDP}} \Delta LIFEEXP$, where ΔLIFEEXP is the finite change in life expectancy.

[17] In addition, this model assumes that the responses to the conjoint choice questions are independent within a respondent. This assumption is reasonable, because, as discussed below, a random effects probit model finds no evidence of a significant correlation between the responses.

statistical nature, and means that it is reasonable to pool the data and fit probit models with one vector of coefficients β for the responses to all of the four choice tasks.[18]

We report the results of two such models in table 6. Model A is an independent probit model, while model B is a random-effects probit. In both models, expected adaptive capacity depends only on country attributes.

Table 6--Probit Model Results. N=100 respondents, total number of observations 386.

Variable	Model A: Independent Probit		Model B: Random-Effects Probit	
	Coeff.	T statistic	Coeff.	T statistic
ONE	-0.1046	-1.2558	-0.1023	-0.9298
INCOME	5.59E-05	5.3674	6.07E-05	5.1523
HIGHINEQ	-0.25516	-2.3957	-0.2829	-2.2073
PCT65	-0.01916	-1.0670	-0.0220	-1.2027
LIFEEXP	0.0021	0.1463	0.0028	0.1932
DOCTORS	0.0013	1.1888	1.40E-03	1.1184
UNIVERSA	0.7173	5.8917	0.7454	5.4462
HIGHINFO	0.7886	6.9080	0.8480	6.8674
Correlation rho between error terms in random effects model			0.1090	1.1964
Log likelihood	-214.93		-214.01	

Legend: INCOME= per capita income in US dollars; HIGHINEQ= high inequality in the distribution of income (dummy); PCT65= percentage of the population older than 65; LIFEEXP= life expectancy at birth; DOCTORS= number of physicians per 100,000; UNIVERSA= universal health care system coverage (dummy); HIGHINFO= high access to information via newspaper, television, radio, internet (dummy).

The results for model A show that adaptive capacity is judged to increase with income per capita, and decrease with inequality. The coefficients on these variables are large and significant at the 1% level or better. They imply, for example, that, all else the

[18] The log likelihood function for the pooled data model (restricted likelihood) is -214.93. When the same probit equation is fit to the responses from the first two choice questions (196 observations), we get a log likelihood function equal to -104.83. A probit model of the responses to the last two choice questions (190 observations) produces a log likelihood function of -107.02. The likelihood ratio statistic is, therefore, 6.16 (p-value = 0.62).

same, raising per capita income by $5,000 increases the likelihood that a country is selected as the country of higher adaptive capacity by 68%.

By contrast, the age distribution and life expectancy at birth of the population are not significant predictors of the probability of choosing a country, even though the signs of the coefficients on these variables (negative and positive, respectively) are consistent with our expectations. There are two possible explanations for these results. The first is that our respondents may have thought that unfavorable levels of these factors would be offset by sufficient resources, and would thus be only of secondary importance relative to per capita income. Alternatively, our respondents may have thought that the age distribution of the population and its life expectancy capture sensitivity, but not adaptive capacity.[19]

Regarding the type and quality of the health care system, our respondents indicate that they associate a universal coverage system with a higher degree of adaptive capacity, as is implied by the positive sign of the coefficient on this dummy. The effect is strongly statistically significant (t statistic: 5.89). All else the same, the probability of selecting a country drops to only 0.23 if universal health care is removed. Quality of health care as measured in physicians per capita, however, is not significantly associated with the likelihood of selecting a country over another. High access to information via newspaper, television, radio and internet is associated with a higher adaptive capacity.

As shown in model (B) of table 6, we find no evidence of random effects. The coefficient of correlation between the error terms underlying the choice responses within

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[19] Brooks et al. (2005) identify life expectancy at birth as a key indicator of vulnerability to the human mortality effects of extreme weather events, providing support for this possible interpretation of the statistical insignificance of the coefficient on life expectancy at birth.

an individual is pegged at 0.11, and is not statistically significant. A likelihood ratio test (1.84, p value=0.17) confirms that the model can be simplified to the independent probit.

We experimented with adding (i) individual characteristics of the respondents, such as a gender dummy and dummies for the professional background of the respondent, and (ii) interactions between selected country attributes and professional background dummies in both the independent and the random effect probit, but LR tests indicated that the coefficients of these newly added variables were not different from zero.[20]

VII. Implications of the Responses to the Conjoint Choice Questions.

We use the results of our probit regressions for two purposes. First, we compute the marginal "income-equivalent" of each country attribute. Second, we compute a simple index of adaptive capacity and illustrate its use with a sample of countries from Europe and Central Asia.

The marginal "income-equivalent" of an attribute is computed by dividing the probit coefficient on that attribute by the coefficient on GDP. The results of the probit model A, table 6, imply that a more equitable distribution of income is worth roughly \$4600 in per capita income. For comparison, this is almost equal to the difference between the per capita incomes of the Czech Republic and Spain in 2000. Removing universal health care and replacing it with a private health insurance system would

[20] For example, when we add a gender dummy and dummies for the professional background of the respondent in the independent probit model the appropriate LR statistics is 5.18 (4 degrees of freedom, p-value=0.27). Similar results were obtained when we added (income×engineer), (life expectancy×public health official) and (physicians per 100,000×medical doctor)) to see if respondents tended to weigh more heavily country attributes that might appeal or relate to their professional background. The results of these runs are displayed in Appendix B, along with those of the random-coefficient logit model. Interactions between attributes (e.g., income and share of the elderly in the population, income and life expectancy) were also attempted, but found to be insignificant.

require an increase in per capita income of about \$12,800 to keep adaptive capacity the same. A change from low to high access to information is considered equivalent to a change in per capita income of \$14,107.

These figures show clearly that universal health care and access to information are judged crucial determinants of adaptive capacity: it takes a very large increase in resources to compensate for their absence, and they are judged as roughly equivalent to one another.[21] (Fortunately, GDP per capita, life expectancy, and physicians per 100,000 are easily obtained from the World Bank and other official databases, while information on health care systems based on universal coverage or private insurance can be obtained at http://www.euro.who.int/InformationSources/Evidence.[22])

Based on the random adaptive capacity model and the probit equation, we compute the following simple index of adaptive capacity:

$$AC_l = \mathbf{x}_l \hat{\boldsymbol{\beta}} \tag{10}$$

where l denotes the country of interest and $\hat{\boldsymbol{\beta}}$ is the vector of probit coefficients.[23] One difficulty in computing this index is that we must create indicators for high or low inequality in the distribution of income, and high or low access to information.

[21] That the presence of a universal health care system is judged so vital may well reflect the composition of our sample, which is comprised primarily of European nationals and has very few respondents from the US, a country that does not have universal health care coverage and that tends to feel strongly against such a system. Had our study relied on a US-based sample, we would perhaps reach the opposite conclusions. Also see Appendix B.

[22] When we were unable to locate information about a country's universal versus private health care coverage, we relied on the ratio of private to public health care expenditures from the World Development Indicators database. In countries with universal health care coverage, this ratio is less—generally much less—than one (for good measure, we chose a cutoff ratio of 0.7). Absent specific information about a country's institutional setup, we formed a prediction based on this ratio and on the 0.7 cutoff.

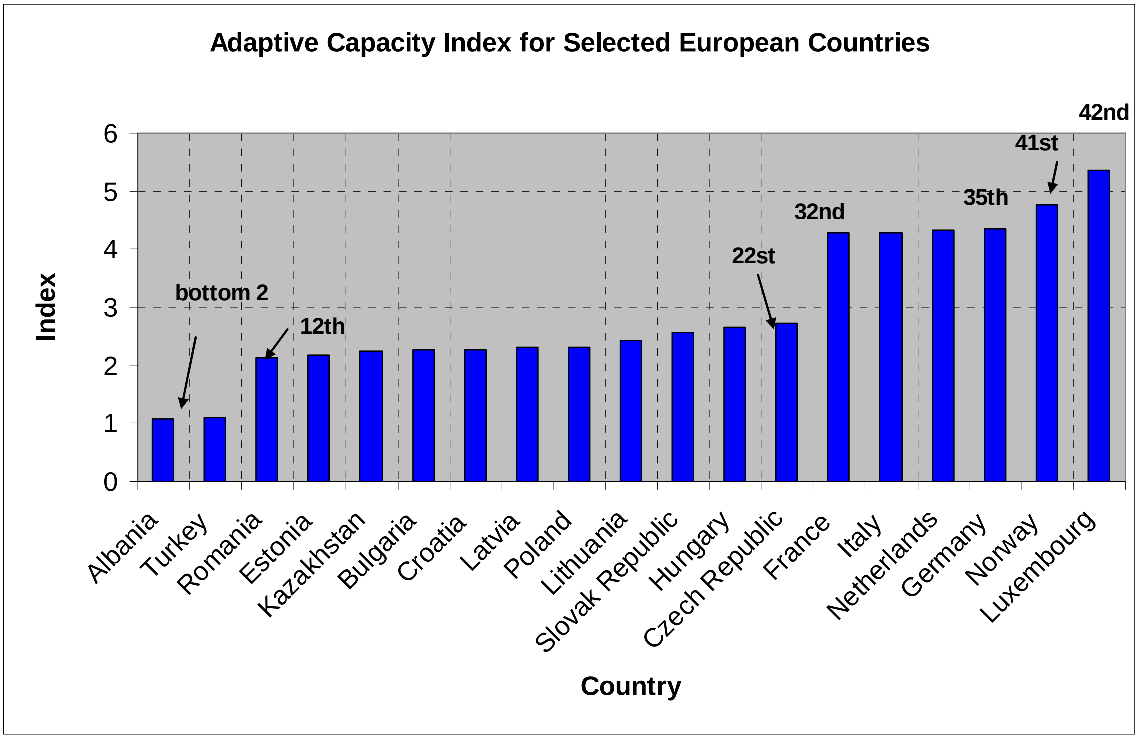
[23] This index is defined between negative and positive infinity, as is implied by the probit model. We do not try to normalize it to make it lie within a specified range.

The most common measure of income inequality is the Gini coefficient, which ranges between 0 (perfect equality, where everyone equally shares resources) and 1 (perfect inequality, where one has all the income, and everyone else has zero income)(available from the World Bank's World Development Indicators database). Countries with a Gini index of 0.50 or more have relatively high inequality in the distribution of income (Oshima and Mason, 2001, Sadrieh and Verbon, 2005, Taylor and Mokhawa, 2003). Following this practice, we therefore construct an indicator equal to one if a country's Gini index is 0.50 or more, and zero otherwise (Leith, 2005).

Regarding access to information, we proxy it with total telephone lines (landline and mobile phones), and assign a value of one to the high access dummy if a country's total number of phones per 1,000 residents is greater than 900. (Adger and Vincent (2005) also use the number of telephones per 1,000 residents to proxy institutional stability and wellbeing in their calculation of the Social Vulnerability Index for African countries).

We report the adaptive capacity indices for selected European and Central Asian countries based on these assumptions in Figure 1, where index values imply higher adaptive capacity. This figure shows that the country with the lowest adaptive capacity in Europe and Central Asia is Albania, where the index is equal to 1.076. The one with the second lowest adaptive capacity index is Turkey (1.079). The former Soviet Republics score poorly, the former Eastern Bloc countries such as the Czech Republic and former Yugoslavia republics are in the middle of the pack, and the wealthier Western Europe countries are the ones with the highest adaptive capacity scores, due to their high incomes, universal health care coverage, and high access to information. The countries with the highest adaptive capacity scores are Norway and Luxembourg.

Figure 1. Adaptive capacity index for 42 Europe and Central Asia countries. Higher index values mean higher adaptive capacity.



Although our assumptions about what constitutes high/low inequality and high/low access to information are arbitrary, the countries' rankings in terms of adaptive capacity are generally robust to changing these assumptions. We arrived at this conclusion after experimenting with all possible combinations of (i) a more stringent definition of high inequality in the distribution of income (a country has an inequitable distribution if its Gini coefficient is greater than 0.31, the average in Europe and Central Asia),[24] and (ii)

[24] In recent decades, countries have tended to converge to a Gini coefficient of about 0.40, and indeed the average Gini coefficient for countries in Europe and Central Asia is about 0.31. Under this alternative classification, Russia is regarded as a high inequality country, whereas it was not considered so in our base

an alternative definition of access to information which considers a country to have high access if the number of landline and mobile phones per 1,000 residents is greater than 370, Europe's average from 1990 to 2002.

VIII. Are the Experts Right?

To answer this question, we use a panel of data from over 100 countries covering the years 1990-2003 and estimate the regression equation:

$$(11)\quad \ln(y_{lt}+1)=\gamma_0+\mathbf{E}_{lt}\boldsymbol{\gamma}_1+\mathbf{S}_{lt}\boldsymbol{\gamma}_2+AC_{lt}\gamma_3+(AC_{lt}\times\mathbf{S}_{lt})\boldsymbol{\gamma}_4+\mathbf{A}_{lt}\boldsymbol{\gamma}_5+\varepsilon_{lt}$$

where y is our measure of vulnerability—country l's deaths in extreme weather events per million people in year t;[25] **E** is a vector of variables thought to capture exposure, **S** is a vector of proxies for sensitivity, AC is our adaptive capacity index calculated for country l in year t,[26] and **A** is a vector of other proxies for adaptive capacity. The γs are vectors of unknown regression coefficients, and ε is the econometric error term.

We posit that the error term is comprised of two components that are normally distributed and independent of each another and of the regressors. One is a country-

calculation. The new classification widens the adaptive capacity gap between Russia (low income and high inequality) and Norway (high income and low inequality), but generally preserves the ranking of countries. The only exception is Turkey, which does poorly in our base calculation but rises dramatically through the ranks in the alternative calculations.

[25] We use the log of (y+1) because about 53% of the observations on the counts of fatalities are equal to zero. Because of the large share of zero in the sample, we initially fitted a tobit model. The tobit model gives qualitatively similar results to the linear regression we report in this paper, but does not fit the data as well as the semilog model.

[26] In this equation, we rely on a more parsimonious specification of the probit model than the one shown in table 5. Specifically, we omit physicians per 100,000, the percentage of the elderly in the population, and life expectancy at birth, which were not significant determinants of the experts' choices between countries. For the purpose of creating the adaptive capacity index, we regress the country selected by the respondents on an intercept, GDP per capita, the inequality dummy, the universal health care coverage dummy, and the high access to information dummies. The probit coefficients are -0.117346, 0.0000502, -0.190206, 0.724698, and 0.746632, respectively.

specific term, while the other is a completely random component: $\varepsilon_{lt} = \nu_i + \eta_{it}$, which makes equation (11) a random-effects model (see Greene, 2003).

Data sources and a description of the regressors are provided in table 7. Two caveats about the data are in order. First, the mortality data should be interpreted with caution, due to the possible underreporting of death counts for certain countries and years.[27] This one reason for including geographical region dummies in the right-hand side of equation (11), and for adopting the random-effects specification. Second, although we assembled data on losses of lives in extreme weather events for 218 countries, due to missing values for the regressors the specifications of table 7 rely on 143 and 123 countries, respectively.

Table 7 - Variables used in the regression.

Category	Description	Data source
Dependent variable	Log(ndeaths+1), where Ndeaths=fatalities in extreme weather events (floods, windstorms, extreme temperature, slides, wildfires, wave surges) per million residents in year t	Emergency Events Database (EM-DAT), Center for Research on the Epidemiology of Disasters (CRED), University of Louvain.*
E (exposure)	Geographical dummies; CUMDISASTERS (number of extreme event disasters 1960-1989 per 1000 square km)	 EM-DAT
S (sensitivity)	Density (population per square kilometre); Urban (percentage of the population that lives in urban areas); Pop65 (percentage population older than 65)	World Development Indicators (WDI)
A (other determinants of other capacity)	GDP per capita (1995 constant dollars); POLITY2 (variable that ranges from -10 to 10, where -10=high autocracy and 10=perfect democracy)	WDI Center for International Development and Conflict Management, University of Maryland

* The events documented in EMDAT are disasters with 10 or more people reported killed, 100 or more people affected, a call for international assistance, or a declaration of a state of emergency.

Briefly, we account for exposure using geographical dummies and the CUMDISASTERS, the count of extreme weather events normalized by area from 1960 to 1989.[28] CUMDISASTERS may, however, also pick up adaptive capacity, if those countries that are hit by extreme weather frequently have increased their preparedness for such events. A natural disaster that occurs in a highly populated area has the potential to affect a multitude of people, which is why we proxy sensitivity with density and share of the population that lives in urban areas (URBAN). The IPCC argues that sensitivity to many extreme weather events depends on the share of elderly in the population. O'Brien et al. (2004) sound a common theme in their analysis of adaptive capacity and vulnerability to climate stresses in Norway, and in the recent Hurricane Katrina, 74% of the victims were over 60 years old (Simerman et al., 2005), so we enter in the model the share of the elderly in the population (POP65). All else the same, we would thus expect the signs on URBAN and POP65 to be positive.

Possible proxies for adaptive capacity are log income per capita, our adaptive capacity index, and POLITY2, a variable that captures institutions, political processes, possibly the government's willingness to provide assistance in the event of disasters, and—albeit imperfectly—social capital.[29] We expect a negative relationship between

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[27] To put in Yohe and Tol's words "If no life loss is reported in a country like Denmark, then one can be reasonably certain that indeed no one was killed. If no life loss is reported in, say, Zaire, this may be because deaths were overlooked."

[28] Skidmore and Toya (2002) find a positive correlation between this measure and 1960-90 growth in GDP per capita, after controlling for initial level of development, initial education, fertility, government consumption spending, and change in trade flows. They reason that propensity to experience climatic disasters may lower the returns on physical capital, thus discouraging investment in this type of capital and increasing the attractiveness of investment in human capital, which in turn increases growth in the long run. Disasters may also provide opportunities to adopt new technologies. The association between growth and *geological* disasters (e.g., earthquakes) is negative and insignificant.

[29] The IPCC (2001) defines social capital as the network of social relationships, collective social capacities and institutions. Putnam (1995) describes social capital as the features of social life—networks, norms and trust—that enable participants to act together more effectively to pursue shared objectives. Social capital is sometimes proxied with the number of formal organizations, the number of registered non-governmental

income and death rates, but are a bit more agnostic about the sign of POLITY2. First, it has been argued that democratic and participatory processes can sometimes slow down adaptation measures and hinder centralized adaptive planning (Adger, 2000; Yohe and Tol, 2002). In addition, POLITY2 assigns a score of 10 to perfect democracies, -10 to completely autocratic regimes, and scores around -7 or -8 to socialist regimes.

We report the results of two alternative specifications for regression (10) in table 8. Both are estimated by generalized least squares (GLS), the appropriate estimation technique in the presence of random effects (see Greene, 2003). The two specifications differ solely for the regressors used to capture adaptive capacity: specification A uses log GDP per capita and POLITY2, whereas specification B drops the latter and replaces it with the adaptive capacity index based on expert judgment, plus its interaction with the share of the elderly in the population.[30] The purpose of including interactions in the right-hand side of the model is to better capture the dependence of sensitivity (and exposure) on adaptive capacity shown in equation (1).

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organizations, newspaper readership and voting propensity, but we were able to find data of this kind only for a small subset of the countries in our econometric analysis. At any rate, Pelling and High (2005) caution that these variables should be supplemented with micro- and cross-scale analyses and measures.

[30] POLITY2 is highly correlated with our adaptive capacity index (correlation coefficient 0.51), which implies that the latter does a good job of capturing institutions, social capital, etc. Since POLITY2 is correlated with both income per capita (correlation coefficient 0.4) and the adaptive capacity index, we omit it from specification B to reduce the problem of collinearity among regressors.

Table 8 -- Vulnerability regression results (equation 10). Dependent variable: log(ndeaths+1).

Description	A: Specification with POLITY2 (GLS)		B: Specification with adaptive capacity index (GLS)		C. Specification with POLITY2, only countries with GDP per capita > 13,000 (OLS)		D. Specification with adaptive capacity index, only countries with GDP per capita > 13,000 (OLS)	
	Coeff.	t stat	Coeff.	t stat	Coeff.	t stat	Coeff.	t stat
Intercept	1.415551	4.44	1.171955	2.94	2.221556	1.43	0.556911	1.26
Location dummies:								
Sub-Saharan Africa	-0.52889	-2.18	-0.49209	-1.98	-0.24782	-1.41	-0.06108	-0.39
East Asia and Pacific	0.199767	0.82	0.312887	1.29	-0.34094	-2.1	-0.14038	-0.98
Europe and Central Asia	-0.28762	-1.24	-0.22012	-0.97	-0.38198	-1.83	-0.28935	-1.35
Middle East North Africa	-0.24333	-1.01	-0.16697	-0.67				
Latin Am and Carib	-0.0129	-0.05	0.040249	0.16				
South Asia	0.336671	1.18	0.648239	2.13				
Cumdisasters	-0.05602	-0.95	-0.02079	-1.25	-0.1138	-0.28	-0.02506	-1.3
Population density	0.000727	2.66	0.000379	1.35	0.000651	1.71	0.000495	1.54
URBAN--Share of the population living in urban areas	0.000788	0.37	0.002702	1.03	-0.0024	-0.63	-0.00312	-0.81
POP65--Share of the population older than 65	-0.01104	-0.92	-0.01523	-1.02	0.057486	2.58	0.032199	1.46
POLITY2	0.011455	3.13			-0.04087	-2.34		
Log GDP per capita (constant 1995 dollars)	-0.10339	-2.88	-0.08847	-1.55	-0.18992	-1.25	-0.20943	-2.35
AC--adaptive capacity index			-0.60169	-2.5				
AC × pop65			0.044703	3.05				
Number of countries	143		123		24		24	
Number of observations	1914		1656		287		298	
R square	0.1292		0.1327		0.05		0.03	

In both regressions (A) and (B) of table 8, fatalities in extreme weather events vary across regions,[31] increase significantly with population density, and are only weakly associated with the degree of urbanization.[32] The coefficients on previous climatic disasters are negative, suggesting that, if anything, the effect of increased preparedness is

[31] Wald tests reject the null hypothesis that the coefficients on the regional dummies are jointly equal to zero in both (A) and (B). The Wald statistics are 87.03 and 76.10, respectively, with p values smaller than 0.0001.

[32] Lagrange Multiplier (LM) tests reject the null that there are no random effects. The LM statistics are 47.96 and 55.49, respectively, with p values smaller than 0.0001.

slightly prevalent over the effect of increased exposure. However, these coefficients are insignificant at the conventional levels.

We had expected the share of the elderly population to enter in the regression with a positive coefficient, assuming that this variable captures sensitivity. Instead, the coefficient on this variable is negative and insignificant in both runs. As expected, the coefficient on log GDP per capita is negative and significant at the conventional levels in (A). Resources reduce vulnerability, although the effect is less than proportionate: the model predicts that for an average South Asian country, for example, a 10% growth in GDP per capita income reduces the mortality rate by 3.3%. The coefficient on POLITY2 in specification (A) is positive. Although this not an implausible sign (we had expected it to be the net result of offsetting effects), we are a bit surprised by the level of statistical significance for this positive coefficient.

Moving to specification (B), we find that income is less strongly associated with vulnerability, but the coefficient on this variable retains its negative sign. The adaptive capacity index based on the experts' judgements works well, in the sense that higher adaptive capacity significantly reduces fatalities, and that this variable has additional explanatory power even after one controls for income, sensitivity and exposure. Adaptive capacity remains a significant predictor of fatalities even after one excludes log GDP from the regression, and accounts for a relatively large share of the explanatory power of the regression.[33] [34]

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[33] If log GDP per capita is excluded from the regression, the R^2 of the regression is almost unchanged and still around 0.13. However, if adaptive capacity is excluded, the R^2 of the regression drops to only about 0.08.

[34] The coefficients of table 7, column (B), can also be used to illustrate the consequence of unrealistic assumptions about the adaptive capacity of less developed countries: if somehow a South Asian country

Because adaptive capacity is truly meaningful in the presence of elevated sensitivity and exposure to climatic disasters, we experimented with several interactions between the adaptive capacity index and CUMDISASTERS, POP65, and DENSITY. In the end, we found that only one of them enters significantly in the regression—that with POP65, which, as shown in specification (B), is positive (we had expected it to be negative, and we had expected the coefficient on POP65 to be positive).

One concern with regressions (A) and (B) is that for countries with levels of income well below those covered by the conjoint choice questions, the adaptive capacity index is essentially an out-of-sample, and thus poor-quality, prediction. In regressions (C) and (D), we exclude from the sample observations with income per capita below 13,000 dollars.

This time, there is no evidence of random effects, and the models are estimated by OLS. Model (C) is analogous to (A) but based on the restricted sample. This time POLITY2 and log income per capita are both negatively associated with vulnerability, and the coefficient on POLITY2 is significant. Model (D) is a simplified variant of (B), with the adaptive capacity index negative and strongly significant. (Log income and the interactions were excluded from this model because they were insignificant, a result we attribute to their correlation with the adaptive capacity index.) In sum, we conclude that the adaptive capacity index does show the expected relationship with vulnerability.

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were able to achieve, all else the same, a level of adaptive capacity similar to that of the average European/Central Asian country, it would be able to reduce mortality rates in climatic disasters by 49%.

IX. Discussion and Conclusions

We have illustrated a novel approach for constructing an index of adaptive capacity to certain effects of climate change on human health, and have used it to assess adaptive capacity for actual countries around the world. The index confirms that wealthy Western countries, including most European Union nations and the United States, have high adaptive capacity. These nations are trailed by transition economies and countries that recently joined the European Union (they have lower incomes), whereas former Soviet Republics do considerably worse, due to their low incomes, high inequality in the distribution of income, and, in many cases, failure to provide universal health care coverage. These problems are even more severe in many Asian, African and Latin American countries.

Worldwide, we indeed find that the countries with the lowest adaptive capacity are predominantly in Africa (e.g., Mozambique, Malawi, Sierra Leone, Guinea-Bissau, Tanzania, Niger, Burkina Faso). Some of the poorest Asian and central Asian countries are also predicted to have low adaptive capacity. Many of the countries we find to have extremely low adaptive capacity also appear on the lists of the most and of moderately-to-highly *vulnerable* countries developed by Brooks et al. (2005), who elicit rankings from a panel of seven experts to examine how their summary measure of vulnerability varies with the weights assigned to the 11 indicators it is formed with. This overlap provides empirical support for the notion that communities and countries with least resources have the least capacity to adapt and are thus the most vulnerable (Haddad, 2005). Additional evidence that our index is plausible comes from the fact that it is negatively correlated, the correlation coefficient being -0.43, with the Social Vulnerability Index created by Adger and Vincent (2005) for African nations.

A subsequent regression using panel data from many countries for 1990-2003 indeed shows that our adaptive capacity index is negative correlated with vulnerability, where vulnerability is the log of deaths in climatic disasters in country *l* in year *t*, normalized by population. Although explaining climatic disaster fatalities is generally difficult (the R^2 of our regressions do not exceed 0.13), the adaptive capacity index account for a relatively large share of the explanatory power of the regression, even controlling for the country's GDP per capita.

Although this study focuses on national-level assessments, it does provide some insights on the local effects of some recent extreme weather events. For example, the recent loss of lives in New Orleans during and after Hurricane Katrina illustrates the importance of an unequal distribution of income, autocratic response, access to information, and an accessible public health care system. Evacuation plans in New Orleans differed by residents' "income-level, age, access to information, access to private transportation, their physical mobility and health, their occupations and their social networks outside of the city" (Fussell, 2005). Among other things, these considerations provide support for O'Brien et al.'s claim that there may be highly vulnerable local communities within wealthy countries that would be otherwise concluded to have high adaptive capacity.

Based on these results, we conclude that conjoint choice questions, such as the ones proposed and applied in this paper in the context of adaptive capacity, work well as an approach for eliciting expert opinions. They could be applied as an alternative to, or in conjunction with, other expert elicitation techniques, such as ratings and rankings (Brooks et al., 2005), to study other aspects of climate change (Nordhaus, 1994; Morgan et al., 2001), and/or mitigation or adaptation policies.

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Appendix A. Questionnaire. (provided in separate document)

Appendix B. Additional models of the responses to the conjoint choice questions.

B.1. Results of independent probit models that control for the professional background of the respondents or include interactions between attributes.

Table B.1. Independent probit model of the responses to the conjoint choice questions. N=100 respondents, total number of obs.= 386.

Variable	(I) Profession dummies (additive form)		(II) Interactions with profession dummies		(III) Interactions between attributes	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
ONE	-0.2422	-1.7434	-0.1134	-1.3542	-0.1312	-1.514
INCOME	5.73E-05	5.3927	5.34E-05	4.8651	.5.93E-05	5.487
HIGHINEQ	-0.2665	-2.4847	-0.2522	-2.3607	-0.2564	-2.401
PCT65	-0.0197	-1.0913	-0.0185	-1.0269	-0.0094	-0.489
LIFEEXP	0.0029	0.2034	-0.0107	-0.6910	0.0056	0.359
DOCTORS	0.0014	1.3087	1.11E-03	0.9891	0.0013	1.194
UNIVERSA	0.7241	5.8637	0.7271	5.9405	0.7754	5.962
HIGHINFO	0.7903	6.8299	0.7741	6.7256	0.7779	6.705
MALE	0.1504	0.9771				
MEDICAL	0.2392	1.2644				
PUBLICHE	0.0570	0.2778				
ENGINEER	-0.0797	-0.3567				
INCOME1			2.10E-05	0.8915		
DOCTOR1			0.00012	0.0520		
LIFEEXP1			0.0719	2.0739		
INCOME×PCT65					0.32E-05	1.283
INCOME× LIFEEXP					0.79E-06	0.441
Log likelihood	-212.34		-212.32		-213.78	

Legend: INCOME= per capita income in US dollars; HIGHINEQ= high inequality in the distribution of income (dummy); PCT65= percentage of the population older than 65; LIFEEXP= life expectancy at birth; DOCTORS= number of physicians per 100,000; UNIVERSA= universal health care system coverage (dummy); HIGHINFO= access to information via newspaper, television, radio, internet (dummy); MALE= male (dummy); MEDICAL= medical field (dummy); PUBLICHE= public health or epidemiology field (dummy); ENGINEER= engineering field (dummy); INCOME1= income×engineer; DOCTOR1= life expectancy×public health officials; LIFEEXP1= physicians per 100,000×medical doctor.

B.2. Random-coefficient Logit Model.

If we assume that η in equation (6) follows the standard logistic distribution, instead of being normally distributed, we obtain a logit model in lieu of a probit. In the logit model, the probability of selecting option 1 is expressed as:

(B.2.1) $$\Pr(1) = \exp(\mathbf{x}_{i1}\boldsymbol{\beta}) / \left[\exp(\mathbf{x}_{i1}\boldsymbol{\beta}) + \exp(\mathbf{x}_{i2}\boldsymbol{\beta})\right].$$

Because the logistic distribution is very similar to the normal distribution, logit models tend to give results that are similar to those of the corresponding probit models. Equation (B.2.1) can be amended to allow the β coefficients be random variables, rather than fixed constants. For respondent *i*, $\boldsymbol{\beta}_i = \overline{\boldsymbol{\beta}} + \mathbf{u}_i$, where $\overline{\boldsymbol{\beta}}$ is the expected value of $\boldsymbol{\beta}_i$, and $\mathbf{u}_i$ is a vector of random terms that represents the deviation between the individual's own vector of coefficient and their expected value. Conditionally on $\mathbf{u}_i$, the probability of choosing alternative 1 is thus:

(B.2.2) $$\Pr(1 \mid \mathbf{u}_i) = \frac{\exp(\mathbf{x}_{i1}\boldsymbol{\beta} + \mathbf{u}_i)}{\left[\exp(\mathbf{x}_{i1}\boldsymbol{\beta} + \mathbf{u}_i) + \exp(\mathbf{x}_{i2}\boldsymbol{\beta} + \mathbf{u}_i)\right]}.$$

Since, however, **u** is typically not known, it is necessary to integrate (B.2.2) with respect to the joint density of $\mathbf{u}_i$, $f(\mathbf{u}_i)$, to obtain the unconditional probability of selecting alternative 1:

(B.2.3) $$\Pr(1) = \int \ldots \int \frac{\exp(\mathbf{x}_{i1}\boldsymbol{\beta} + \mathbf{u}_i)}{\left[\exp(\mathbf{x}_{i1}\boldsymbol{\beta} + \mathbf{u}_i) + \exp(\mathbf{x}_{i2}\boldsymbol{\beta} + \mathbf{u}_i)\right]} f(\mathbf{u}_i) d\mathbf{u}_i .$$

Examination of equation (B.2.3), which is the contribution to the likelihood in a random-coefficient logit, shows that in order to estimate the random-coefficient logit, it is necessary to make assumptions about the distribution of **u**, and to decide whether all or only some of the elements of β should be random.

We experimented with different assumptions about (i) which subset of the β coefficients should be treated as random and (ii) the distribution of $\mathbf{u}_i$, and in the end we found that the only coefficient that lends itself to being interpreted as a random variable is that on universal coverage of the health care system. The estimation results are reported in table B.2.2., and are qualitatively similar to specification (A) in table 6.

Table B.2. Logit and random-coefficient logit model of the responses to the conjoint choice questions. N=100 respondents, total number of obs.= 386.

	Independent logit			Random-coefficient logit (random coefficient on UNIVERSAL and HIGHINFO; both are assumed normally distributed)					
Variable	coefficient	t statistic		coefficient	t stat	mean of coeff. if random	t stat for mean of random coeff.	standard deviation of coeff. If random	t stat for standard deviation of random coeff.
Intercept	-0.15149	-1.088		-0.094658	-0.482				
INCOME	.93ED-04	5.252		0.0001443	3.495				
HIGHINEQ	-0.44109	-2.419		-0.773442	-2.046				
PCT65	-0.02908	-0.945		-0.05782	-1.2				
LIFEEXP	0.002785	0.116		0.0154185	0.455				
DOCTORS	0.002256	1.24		0.003677	1.264				
UNIVERSA	1.214709	5.707				1.951884	2.997	2.39006319	2.003
HIGHINFO	1.320657	6.597				2.099106	2.806	1.4930525	1.131
log L	-215.03			-213.039					