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Analysis

The impact of climate on life satisfaction

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ABSTRACT

We analyse the influence of climate on average life satisfaction in 79 countries using data from the World Values Survey. Climate is described in terms of 'degree-months' calculated as the cumulated monthly deviations from a base temperature of 65 °F (18.3 °C). Our results suggest that countries with climates characterised by a large number of degree-months enjoy significantly lower levels of life satisfaction. This finding is robust to a wide variety of model specifications. Using our results to analyse a particular climate change scenario associated with the IPCC A2 emissions scenario points to major losses for African countries, but modest gains for Northern Europe.

1. Introduction

There are many reasons why households might prefer one sort of climate rather than another. Climate impacts domestic heating and cooling needs. Climate alters people's calorific requirements. Different types of climate necessitate different types of clothing. Climate constrains outdoor leisure activities. Sociological, psychological and physiological studies have demonstrated that certain climates are conducive to health and wellbeing. Parker (1995) identifies 830 sociological studies, 458 psychological studies and 807 physiological studies concerning the effects of climate on human functioning. More formally, otherwise identical households inhabiting different climates are likely to have different levels of utility because climate alters the cost of producing 'service flows' of interest to households (Becker, 1965).

It is possible to measure in monetary terms the impact on households of a change in climate. The appropriate measure will depend on perceived property rights and the direction of change. Assuming rights to the existing climate, for a move to an inferior climate the appropriate measure is minimum willingness to accept compensation (WTA). For a move to a superior climate the appropriate measure is maximum willingness to pay (WTP). Together, these are the compensating surplus (CS) measures of welfare change. The purpose of this paper is to estimate the influence of climate on life satisfaction using cross country data from the World Values Survey 1981–2008 and then to use the results to estimate the CS for a given climate change scenario.

Estimates of CS for a change in climate are of interest to those engaged in cost benefit analyses (CBA) of climate policy e.g. Stern et al. (2006) and Nordhaus (2008). The belief that CBA can inform climate policy is not universally shared. And in any case, estimates of CS that we will present ignore impacts arising from changes in prices or GDP per capita.[2] For a recent review of climate change damage cost estimates see Tol (2009). Tol categorises this literature distinguishing (a) approaches attempting to value separately particular climate change impacts prior to aggregating them and those not actively seeking to attribute damage costs to different impacts; (b) studies confining themselves to market impacts and others dealing with the nonmarket impacts; (c) studies explicitly modelling adaptation and those using spatial variation in

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[2] Writing the utility function of a household in location i as $V_i = (P(Z_i), Y(Z_i), Z_i)$ where V is utility, P is a vector of prices and Z is climate we measure the direct effect of Z_i on V_i and not the indirect effect via P and Y. We do not measure the value of a change in climate in alternative location j even if the household does have preferences over Z_j. The analysis also picks up landscape effects if climate favours one type of landscape more than another.

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Table 1
The data. Number of countries = 79, number of observations = 158.

Variable	Mean	Std. dev.	Minimum	Maximum
SATISFACTION	6.58	1.06	3.7	8.4
YEAR	1999	6.51	1981	2008
GDPPC (2005 PPP USD)	12,610	11,331	236	49,415
INFLATION (%)	26.3	104.7	−1.1	1058.3
UNEMPLOYMENT (%)	9.0	6.4	1.2	36.4
POPDEN (persons per km^2)	159.5	506.7	1.9	6186.6
POPULATION	1.02e+08	2.42e+08	845,037	1.32e+09
FREEDOM	2.63	1.67	1	6.5
UNDER 14 (%)	27.2	9.0	13.5	49.4
OVER 65 (%)	8.9	4.8	2.0	19.9
LATITUDE (°)	23.6	28.41	−41	64
COAST_DUMMY	0.85	0.35	0	1
LOW_ELEV (M)	2.9	127.1	−408	950
HIGH_ELEV (M)	3792.5	2214.3	166	8850
TMEAN (°)	15.7	6.3	4.3	28.3
PMEAN (MM)	74.0	41.2	2.0	200.0

climate as an analogue for future climate; and (d) damage cost estimates based on WTP and those based on WTA.

The approach that we will go on to describe in more detail deals exclusively with non-market impacts whilst making use of spatial variations in the existing climate as an analogue for climate change. It deals explicitly with the WTP and WTA concepts. It seeks a comprehensive estimate of nonmarket damages but is unable to attribute these damages to particular impacts e.g. heating and cooling, health etc.

Researchers have already reported that climate provides a statistically significant explanation of cross country variations in measures of subjective wellbeing.[3] That research however, is based on a potentially problematical representation of countries' climates describing them either in terms of annual average temperature and annual average temperature squared; or temperature of the hottest and coldest month.[4] Furthermore research fails properly to control for variables potentially correlated with climate. This paper by contrast describes climate in terms of heating and cooling 'degree-months' (DMs).[5] To anticipate our main findings it appears that, along with GDP per capita (GDPPC), DMs provide a convincing explanation of the cross-country variation in reported life satisfaction.[6]

The remainder of the paper is organised as follows. In the second section we review the literature on the value of climate to households and the economics of subjective wellbeing. In Section 3 we describe the data underlying the empirical analysis. In Section 4 we present a cross country analysis of the determinants of life satisfaction. In Section 5 we use our results to calculate the CS for a climate change scenario associated with the IPCC A2 emissions scenario. The final section concludes.

2. Literature Review

Researchers have employed a wide variety of valuation techniques to estimate the welfare impact of marginal and non-marginal changes in climate.[7] But none have involved asking individuals e.g. "What is the maximum amount your household is willing to pay in order to enjoy a climate similar to that of Nice?" since, although conceptually meaningful, this type of question is regarded as too abstract. Most researchers hoping to estimate the value to households of changes in the climate have instead chosen to use revealed preference techniques. And the majority of these attempt only a national, rather than a Global assessment. The advantage of a global analysis is that including in any analysis countries with very different climates makes it easier to identify the role of climate. Many valuation techniques do not lend themselves to a Global assessment. Below we describe four alternative approaches including the hedonic technique, the household production function approach, the hypothetical equivalence scale approach and the life-satisfaction approach.

The hedonic technique suggests that if households are freely able to select from differentiated localities then climate becomes a choice variable. The tendency will be for the costs and benefits associated with particular climates to become capitalised into property prices and wage rates. The underlying assumption is that migration-induced changes in house prices and wage rates households have eliminated the net benefits of different locations. Nordhaus (1996), Maddison (2001a), Mendelsohn (2001), Maddison and Bigano (2003), Mueller (2005) and Rehdanz and Maddison (2009) all use the hedonic approach to measure the value of marginal changes in climate variables. Cragg and Kahn (1997) adopt a discrete choice random utility modelling framework to examine how migrants trade off climate against disposable net income.

Determining the value of environmental goods using the household production function approach involves specifying an indirect utility function including income, the prices of marketed goods and the quantity of the environmental good as arguments. Using Roy's theorem the corresponding Marshallian demand functions are estimated on expenditure data. The technique assumes that households share the same underlying tastes, and that environmental goods and marketed goods display demand dependency (Bradford and Hildebrandt, 1977). Examples of the household production function approach applied to climate include Maddison (2001b) and Maddison (2003).

In the hypothetical equivalence scale approach a sample of individuals is asked about the minimum level of income necessary, for someone sharing their set of circumstances, to achieve a particular welfare level e.g. "a satisfactory standard of living". Regression analysis reveals what factor respondents implicitly believe mean that their household requires more or less money to reach "a satisfactory standard of living". The underlying assumption of this technique is of course that individuals share a common understanding of what constitutes "a satisfactory standard of living". Van Praag (1988) applies this technique to the European climate.

In order to answer a broad range of questions economists have begun to analyse individual measures of happiness generated by questions such as: "How happy are you on a 1–10 scale?". For an overview of recent advances in the economics of subjective well-being see Stutzer and Frey (2010). Others providing overviews of the state of economic research include Bruni and Porta (2007), Di Tella and MacCulloch (2006), Frey (2008), Layard (2005) and Van Praag and Ferrer-i-Carbonell (2004). Using regression techniques suitable for analysing ordinal data the happiness approach can be used to estimate the value of environmental goods. For examples see Brereton et al. (2008), Ferreira and Moro (2010), Luechinger (2009), Rehdanz and Maddison (2005 and 2008), Van Praag and Baarsma (2005) or Welsch (2002, 2006). This is most simply achieved by examining the marginal rate of substitution between income and the level of environmental goods. Frijters and Van Praag (1998) use this approach to estimate the influence of climate on wellbeing in Russia.

Two papers have already analysed cross country differences in measures of subjective wellbeing using aggregate data to estimate the value of climate.

Van der Vliert et al. (2004) examine how temperature and temperature squared affect nationally averaged measures of subjective

[3] Note that we use the terms subjective wellbeing, utility, life satisfaction and happiness interchangeably.
[4] We describe more fully the limitations of existing research in the next section.
[5] Heating and cooling degree-months (HDMs and CDMs) are closely related to heating and cooling degree-days (HDDs and CDDs). We do not however wish to suggest that the only impact of climate on life satisfaction is through changed heating and cooling requirements. The construction of HDMs and CDMs and their relationship to HDDs and CDDs is explained later.
[6] Although it is not the focus our analysis also provides further evidence on the relationship between economic development and life satisfaction, and provides an estimate of the welfare costs of inflation.
[7] Studies could also be classified according to whether they use cross country data or within country data. With cross country data one obviously has greater variation in climate. This is important if one wishes to identify the existence of a climate optimum. But in cross country studies data is aggregated over large climatically diverse areas leading to a loss of control.

Table 2
Regressions explaining cross-country variation in life satisfaction. Dependent variable = SATISFACTION. Method = OLS.

Variable	Model 1	Model 2	Model 3
	Parameter (T-statistic)	Parameter (T-statistic)	Parameter (T-statistic)
YEAR	−0.00489 (−0.47)	−0.000262 (−0.02)	−0.000805 (−0.07)
LOG(GDPPC)	0.827** (6.55)	0.927** (7.78)	0.915** (8.36)
INFLATION	−0.000871* (−2.36)	−0.000746 (−1.94)	−0.000743 (−1.94)
POPDEN	−0.000168 (−1.97)	−0.000167* (−2.10)	−0.000162* (−2.26)
POPULATION	1.38e-09** (3.27)	1.43e-09** (2.63)	1.37e-09* (2.43)
FREEDOM	0.0249 (0.48)	0.00245 (0.05)	0.00316 (0.06)
UNDER 14	0.0203 (0.99)	0.0393 (1.91)	0.0349 (1.55)
OVER 65	−0.0150 (−0.60)	−0.000521 (−0.02)	−0.00389 (−0.12)
ABSLAT	0.00641 (0.43)	0.0183 (1.26)	0.0211 (1.98)
COAST	−0.188 (−0.87)	−0.250 (−1.26)	−0.271 (−1.30)
LOW_ELEVATION	0.000088 (0.21)	0.000202 (0.56)	0.000200 (0.56)
HIGH_ELEVATION	−0.0000297 (−0.69)	−0.0000337 (−0.74)	−0.0000271 (−0.57)
CDM	−0.0134** (−3.18)	−0.0125** (−3.43)	
HDM	−0.00840 (−1.87)	−0.0104* (−2.32)	
DM			−0.0116** (−3.90)
CONSTANT	8.72 (0.41)	−2.08 (−0.09)	−0.782 (−0.04)
REGIONAL DUMMIES	Yes	Yes	Yes
WEIGHTS	None	Country	Country
R-SQUARED	0.737	0.774	0.774

Note: T-statistics are heteroscedasticity-consistent. Data are clustered at the level of the country. Note that * implies significance at the five % level of confidence and ** implies significance at the one % level of confidence.

wellbeing whilst simultaneously controlling for GDPPC. In total 55 countries were included in their analysis and for large countries temperature data was averaged over major population centres. For poor countries the paper points to an inverted U shaped relationship between subjective wellbeing and temperature. But for rich countries the data point to a U shaped relationship. Such hard to explain results may be due to the absence of any controls apart from GDPPC and in particular, no control for seasonal variation in temperature.

Rehdanz and Maddison (2005) analyse cross-country averages for subjective wellbeing. They use 185 observations from 67 different countries. The dependent variable is measured on a 1–4 integer scale. Simultaneously including a large number of variables Rehdanz and Maddison employ three different specifications of climate: Annual average temperature and annual average temperature squared; the number of hot and cold months; and the temperature of the coldest month and the temperature of the hottest month. Also included is average precipitation and precipitation squared; precipitation in the wettest month and precipitation in the driest month; and the number of wet and dry months. In the preferred specification higher temperatures in the coldest month and lower temperatures in the hottest month increase significantly subjective wellbeing.

Representing the climate by the temperature of the hottest and coldest month means the impact of climate change will be independent of baseline climate; using only annual average temperatures to represent the climate implicitly suggests that individuals are indifferent between climates which might differ substantially in terms of seasonal variation.

Every study seems to characterise the climate in a different way e.g. annually averaged temperatures; the standard deviation of monthly temperatures; January and July average temperatures; the temperature of the hottest and the coldest month; the number of hot and cold months; and HDDs and CDDs. This defeats any attempt to compare the results obtained by different studies. But despite the substantial differences between studies most indicate that people are willing to pay substantial sums to enjoy more preferred climates.[8] To what extent can this evidence reliably inform cost-benefit analyses of climate policy? As we have seen the representation of the climate is sometimes far from persuasive. Revealed preference studies interpret spatial differences in the climate as an analogue for future climates but it may be inappropriate to assume that households will have time perfectly to adapt themselves.[9] Finally, many revealed preference analyses reveal only what current households are willing to pay for a more preferred climate yet the scenario of interest actually involves future households.

3. Data

Data are taken from the World Values Survey (WVS).[10] The data includes 178 observations drawn from 87 countries. Surveys were undertaken over the period 1981–2008. The WVS records the views of respondents on a variety of issues but for our purposes the variable of interest is life satisfaction (SATISFACTION) measured on a 1–10 scale. More specifically, question V22 included in the WVS is

> *All things considered, how satisfied are you with your life as a whole these days? Using this card on which 1 means you are “completely dissatisfied” and 10 means you are “completely satisfied” where would you put your satisfaction with your life as a whole? (Code one number).*

The most satisfied country in the dataset is Puerto Rico in 2001, followed by Colombia in 1998 and Switzerland in 1989. The least satisfied countries are Moldova in 1996, followed by Tanzania and Zimbabwe in 2001. Following Maddison (2003) a linear time trend (YEAR) indicating when the survey was conducted tests for any autonomous changes in life satisfaction caused perhaps by technological progress in households' production functions.

GDP per capita (GDPPC) measured in 2005 PPP USD is taken from the World Bank along with data on INFLATION, UNEMPLOYMENT and POPULATION. Notice that we use GDPPC rather than consumption in order to account for differences in the level of public goods. The unemployment data has many missing values. We include an index (FREEDOM) purporting to measure political rights and civil liberties ranging from 1 (low levels of freedom) to 7 (high levels of freedom).We

[8] Cushing (1987) investigated different specification of climate variables in the context of models of migration within the United States. He found that temperature extremes provided a better representation of the climate than HDDs and CDDs; and that HDDs and CDDs in turn provided a far superior to average temperature and average temperature squared. We believe that temperature extremes might be satisfactory in a single country but not in a cross-country context.

[9] Potential overlap exists with any study attempting to value separately the impact of climate change on the landscape.

[10] See http://www.worldvaluessurvey.org/.

also include data on the percentage of the population under 14 years of age (UNDER14) and over 65 years of age (OVER65).

Data on area used to calculate population density (POPDEN) is taken from the CIA World Factbook. The absolute value of the latitude of each country's centroid is used to control for the variation in hours of daylight over the annual cycle. The dummy variable COAST indicates whether the country is landlocked. The variable LOW_ELEV measures the lowest point of elevation and HIGH_ELEV the highest point of elevation in metres.

Monthly mean temperatures and precipitation totals are taken from a variety of sources, mainly Pearce and Smith (1993) and www.worldclimate.com. Climate data are averaged over two or more major population centres (see Appendix 1 for details). For countries larger than 10,000,000 km^2 (Russia) we took four climate records. For large countries between 1,000,000 and 10,000,000 km^2 e.g. Australia etc. we generally took no more than three climate records. For countries between 100,000 km^2 and 1,000,000 km^2 e.g. Bangladesh we generally took no more than two climate records. For countries less than 100,000 km^2 e.g. Albania we generally took only one climate record. The climate records chosen are always those of the largest cities in a particular country (unless there is no suitable record for that city).

This procedure is inferior to using data from geographically smaller areas. Unfortunately however, although the WVS provides regional information in many instances the region identified by the WVS does not correspond to any officially recognised region. Below we will demonstrate that excluding the climatically most diverse countries does not alter the results. Annually averaged mean temperature (TMEAN) in °C and annually average monthly precipitation (PMEAN) in mm are displayed in Table 1.

Researchers often describe both weather and climate in terms of heating degree-days (HDDs) and cooling degree-days (CDDs). For examples of studies using HDDs and CDDs see Lawrence and Aigner (1979), and Dubin and McFadden (1984). For an early exposition of HDDs and CDDs see Thom (1954). Almost invariably these measure daily deviations from a base mean temperature of 65 °F (18.3 °C). The base temperature is intended to approximate the outside temperature where householders need neither heating nor cooling to feel comfortable indoors. Our analysis uses the analogous concept of heating degree-months (HDMs) and cooling degree months (CDMs). These are defined as follows

$$CDM = POS(TJAN - 18.3) + POS(TFEB - 18.3) + \ldots + POS(TDEC - 18.3)$$

$$HDM = POS(18.3 - TJAN) + POS(18.3 - TFEB) + \ldots + POS(18.3 - TDEC)$$

where TJAN represents mean January temperatures, TFEB represents mean February temperatures etc. and the function POS returns only positive deviations.[11] Below we experiment with HDMs and CDMs calculated using base temperatures other than 65 °F (18.3 °C).

Finally a set of dummy variables is included representing different regions of the World: Eastern Europe; Southern Europe; Northern Europe; Western Europe; North America; Central America; South America; The Caribbean; Northern Africa; Western Africa; Central, Southern and Eastern Africa; Eastern Asia; South-Central Asia; South-Eastern Asia; Western Asia and the Middle East; and Oceania. These are included amongst other things to capture cultural factors which may influence the way in which people respond to questions on life satisfaction.

4. Results

Model 1 in Table 2 includes all the explanatory variables apart from UNEMPLOYMENT in an unweighted OLS regression (Table 2). With missing observations the number of countries reduces to 79. Countries with higher Log(GDPPC) report higher SATISFACTION significant at 1%. The variables INFLATION and POPDEN are significant at 5% whilst POPULATION is significant at 1%. CDMs are significant at 1% whilst HDMs are significant at 10%. Both are negatively signed meaning deviations from 65 °F (18.3 °C) reduce SATISFACTION.

Model 2 is the same regression run using 'country' weights (each country now has the same weight irrespective of the number of times it participated in the WVS). Some countries like Argentina participated five times whereas other countries like Andorra participated only once. The results are almost identical except that HDM is now significant at 5%. Model 3 replaces CDM and HDM with DM. This specification assumes that HDMs and CDMs are equally bad in terms of their impact on SATISFACTION. Compared with Model 2 there is no significant loss of fit not even at 10% ($F(1,78) = 0.15$, $P = 0.697$) and the coefficient on DM is easily significant at 1%. Note that without the variable ABSLAT the t-statistic on DM drops to 2.61. The correlation between ABSLAT and DM is 0.64. We also ran Model 3 with 17 year dummies instead of a linear time trend (in some years no surveys were conducted). The coefficient on the variable of interest DM is hardly changed (−0.0113 compared to −0.0116) and the T-statistic is 3.65 which is still significantly different from zero at the one % level of confidence.

We plotted the leverage of each observation against the squared residual but we were unable to find any influential outliers. We also looked for observations with an absolute studentized residual in excess of 2.5 and then omitted them each in turn. The resulting changes were all very minor. Employing Cook's D statistic we identified Singapore 2002 as the most influential observation. Omitting Singapore 2002 caused only very minor changes in the results and judging by the studentized residuals Singapore is anyway not an outlier. Lastly we used the technique of dfbetas to identify those observations which if dropped would cause the parameter on degree months to increase or decrease by the greatest possible amount. This technique reveals that dropping Tanzania 2001 causes the coefficient on DM to rise to −0.0097 whilst dropping Uganda 2001 would cause the coefficient to fall to −0.0123. Judging by their studentized residuals neither of these observations is an outlier.

We also examined the standardised beta coefficients for Model 3 obtained by subtracting the mean of the explanatory variables and then dividing by their standard deviation prior to conducting multiple regression analysis. Standardised beta coefficients refer to the expected change in the dependent variable per one standard deviation increase in the explanatory variable. Our purpose is to identify which explanatory variables have the greatest effect on the dependent variable, SATISFACTION. The highest standardised beta coefficient is 0.996 for Log GDPPC. The second highest coefficient is for DM with a coefficient of −0.393.

In order to check whether 65 °F (18.3 °C) is the most appropriate base temperature we ran Model 3 again with DMs calculated using different base temperatures. Table 3 summarises the results. The base temperature providing the greatest explanatory power is exactly 65 °F (this finding is obviously conditional on the assumed functional form of the estimating equation).

We now test whether the relationship between DM and SATISFACTION is robust to other changes in model specification (see Table 4).

Along with DM Model 4 includes TMEAN, $TMEAN^2$, the temperature of the coldest month (TMIN), the temperature of the hottest month (TMAX) and the standard deviation of TJAN through to TDEC (TSTDEV). These new variables are not jointly significant at the ten % level of confidence ($F(5,78) = 1.28$, $P = 0.282$). The fact that we cannot reject the null hypothesis does not of course mean that DM is an entirely adequate description of the climate. It does however indicate that Model 3 is a valid simplification of a more general model,

[11] HDMs and CDMs calculated using weather data might differ due to interannual variability of monthly temperatures. But because we do not have access to a sequence of weather data for all 87 countries we are forced to calculate HDMs and CDMs using climate data.

Table 3
The optimal base temperature.

Base temperature	T-statistic on DM
50 °F (10.0 °C)	−1.83
55 °F (12.8 °C)	−2.35
60 °F (15.6 °C)	−3.30
64 °F (17.8 °C)	−3.84
65 °F (18.3 °C)	−3.90
66 °F (18.9 °C)	−3.78
70 °F (21.1 °C)	−1.84
75 °F (23.8 °C)	−0.25
80 °F (26.7 °C)	+0.40

Note: T-statistics are heteroscedasticity-consistent. Data are clustered at the level of the country.

one containing climate variables chosen by other researchers. Nevertheless, the fact that DM is not now individually significant at 10% either points to a high degree of multicollinearity.

Model 5 includes PMEAN, PMEAN^2, mean precipitation of the driest month (PMIN), mean precipitation of the wettest month (PMAX) and the standard deviation of PJAN through to PDEC (PSTDEV). These new variables are not jointly significant even at 10% ($F(5,78)=1.03$, $P=0.407$). Neither the coefficient on DM nor its statistical significance is affected. Model 6 includes unemployment and the number of countries falls to 63. Neither the coefficient on DM nor its statistical significance is affected. Model 7 excludes 15 climatically diverse countries. Climatically diverse countries are identified as follows: For those countries whose climate is a weighted average of more than one climate record we subtracted the minimum temperature from the maximum temperature in the set of climate records to obtain a measure of climatic range. We then sum these measures of climatic range across the entire year to obtain an overall measure of climatic diversity. According to this measure the 15 climatically most diverse countries are: Colombia; the United States; Venezuela; Canada; Brazil; Australia; India; Indonesia; South Africa; Iran; Mexico; Peru; Russia; Saudi Arabia; and Vietnam.[12] Excluding these countries the coefficient on DM increases in absolute terms relative to Model 3 but only very slightly, from −0.0116 to −0.0123.

By including the interaction term Log(GDPPC)×DM Model 8 allows the marginal rate of substitution between GDPPC and DMs to be more or less than proportionate to GDPPC and potentially dependent of the number of DMs. This interaction term is significant at 1%.[13] In fact Model 8 suggests that if the GDPPC equivalent impact on SATISFACTION of a one unit change in DM is measured as a proportion of GDPPC then the effect of a unit change in DM is more pronounced for poor countries than rich ones. Further model specifications not displayed included adding higher order terms for Log(GDPPC) and DM. These were not significant at 10% (the T-statistics are respectively 0.75 and 0.37).

5. Discussion

The most preferred climate is seemingly one where monthly mean temperatures do not deviate much from 65 °F (18.3 °C). According to this criterion the list of countries possessing a 'satisfactory' climate is headed by Guatemala, Rwanda and Colombia whereas the list of countries with an 'unsatisfactory' climate is headed by Russia, Finland and Estonia.

These results do not depend on the weighting scheme adopted or on the existence of influential outliers. They are unaffected by the inclusion of large countries. We controlled for ABSLAT, HIGH_ELEVATION, LOW_ELEVATION and COAST because these variables are potentially correlated with climate. We also included dummy variables identifying different regions of the world but DMs still have an impact on SATISFACTION statistically significant at 1%.

Other macroeconomic variables have a lesser impact on SATISFACTION. Across the different models INFLATION is always negative but not always significant at 5%. In the single model including the variable UNEMPLOYMENT it is negative and significant only at 5%. When climate is excluded both INFLATION and UNEMPLOYMENT are jointly significant at 10% ($F(2,62)=2.54$, $P=0.087$). But when INFLATION and UNEMPLOYMENT are omitted the coefficient on DM and its statistical significance are both unchanged (results not shown).

What do these results say about the possible impact of climate change on different countries? In order to calculate the CS for a change in climate first let the subscript 0 denotes the pre climate change scenario and subscript 1 indicate the post climate change scenario. SATISFACTION in the pre climate change scenario is given by

$$SATISFACTION_0 = \alpha + \beta LogGDPPC + \gamma DM_0 + \delta LogGDPPC \times DM_0.$$

The parameters β, γ and δ represent the respective impact of a unit change in LogGDPPC, DM and LogGDPPC×DM on SATISFACTION whilst α represents the contribution to SATISFACTION arising from all other sources. SATISFACTION in the post climate change scenario is given by

$$SATISFACTION_1 = \alpha + \beta LogGDPPC + \gamma DM_1 + \delta LogGDPPC \times DM_1.$$

CS is implicitly defined by the following equation

$$SATISFACTION_0 = \alpha + \beta Log(GDPPC-CS) + \gamma DM_1 + \delta Log(GDPPC-CS) \times DM_1.$$

Substituting for SATISFACTION$_0$ gives

$$\beta LogGDPPC + \gamma DM_0 + \delta LogGDPPC \times DM_0 = \beta Log(GDPPC-CS) + \gamma DM_1 + \delta Log(GDPPC-CS) \times DM_1.$$

After algebraic manipulation the following emerges

$$CS = GDPPC - \exp\left[\frac{\beta LogGDPPC + \gamma(DM_0-DM_1) + \delta LogGDPPC \times DM_0}{\beta + \delta DM_1}\right].$$

Next we calculate the number of DMs corresponding to the climate change scenario. This involves superimposing the change in temperatures predicted by a global climate model (GCM) corresponding to a particular greenhouse gas (GHG) emissions scenario onto the current climate. In what follows we use the Hadley CM3 model under the SRES A2 emissions scenario 2070–2099.[14] Finally, inserting country specific values for GDPPC, DM$_0$ and DM$_1$ along with the estimated parameter values $\beta=0.4239148$, $\gamma=-0.0577318$ and $\delta=0.0052829$ taken from Model 8 in Table 4 we generate the country specific estimates of CS presented in Table 5. Note that whilst we calculate the change in real GDPPC necessary to hold SATISFACTION at its current levels in the face of predicted changes in the climate our estimates are based on 2008 GDPPC and do not therefore take into account likely changes in GDPPC over time.

Table 5 points to very different outcomes for countries, at least for the climate change scenario under investigation.

In Eastern Europe the direct impact of climate change is uniformly beneficial ranging from an equivalent 3.3% increase in GDPPC for Hungary to a 29.3 % increase for Belarus. The majority of the estimated welfare impacts are moreover statistically significant at either the five

[12] This list is similar, but not quite identical, to the largest countries in the dataset (obvious omissions are Mali; China; Algeria; and Argentina). Notice that climatic diversity only refers to the populated areas of a country.

[13] Note that this model passes the RESET test for functional form $F(1,78)=1.39$, $P=0.242$. In their analysis of subjective wellbeing Van der Vliert et al. (2004) find that the interaction of income and temperature squared is statistically significant at the one % level of confidence.

[14] Results for emissions scenarios A1 and B2 are also available upon request from the authors along with results from three other GCMs.

Table 4
Further regressions. Dependent variable = SATISFACTION. Method = OLS.

Variable	Model 4	Model 5	Model 6	Model 7	Model 8
	Parameter (T-statistic)	Parameter (T-statistic)	Parameter (T-statistic)	Parameter (T-statistic)	Parameter (T-statistic)
YEAR	0.000487 (0.04)	0.000767 (0.06)	0.00739 (0.58)	−0.0116 (−0.97)	−0.00473 (−0.47)
LOG(GDPPC)	0.934** (8.88)	0.960** (8.60)	0.873** (5.63)	1.10** (7.52)	0.423* (2.18)
INFLATION	−0.000597 (−1.62)	0.000766 (−1.69)	−0.000629 (−1.26)	−0.000458 (−1.47)	−0.000842** (−2.00)
UNEMPLOY			−0.0255 (−2.55)		
POPDEN	−0.000195* (−2.53)	0.000110 (−0.89)	−0.0000911 (−1.23)	−0.000151* (−2.31)	−0.000190* (−2.57)
POPULATION	1.34e-09* (2.24)	1.13e-09 (1.75)	1.74e-09** (4.10)	3.16e-09** (7.08)	1.42e-09* (2.13)
FREEDOM	0.0218 (0.35)	0.0185 (0.25)	0.00203 (0.03)	−0.105 (−1.28)	−0.0262 (−0.47)
UNDER 14	0.0338 (1.44)	0.0296 (1.16)	0.0465 (1.70)	0.0221 (0.87)	0.0351 (1.63)
OVER 65	0.00176 (0.05)	−0.0132 (−0.36)	−0.0228 (−0.70)	−0.0305 0.0360 (−0.85)	−0.00372 (−0.12)
ABSLAT	0.0345* (2.62)	0.0224 (1.96)	0.0355** (3.15)	0.0558** (2.94)	0.0183 (1.82)
COAST	−0.357 (−1.80)	−0.330 (−1.69)	−0.244 (−1.04)	−0.247 (−1.15)	−0.224 (−1.04)
LOW_ELEV	0.000333 (0.81)	0.0000561 (0.11)	0.000786 (1.53)	0.000373 (0.95)	0.0000296 (0.07)
HIGH_ELEV	−0.0000192 (−0.41)	0.0000108 (0.28)	−0.0000205 (−0.49)	−0.0000671 (−1.59)	−0.0000307 (−0.64)
DM	−0.00699 (−0.85)	−0.0114** (−3.45)	−0.0133** (−3.69)	−0.0122** (−3.54)	−0.0577** (−3.41)
DM × Log(GDPPC)					0.00528** (2.75)
TMEAN	−0.00166 (−0.01)				
$TMEAN^2$	0.000406 (0.07)				
TMIN	0.167 (0.85)				
TMAX	−0.221 (−0.94)				
TSTDEV	0.312 (0.58)				
PMEAN		0.0104 (0.86)			
$PMEAN^2$		−0.0000247 (−0.55)			
PMIN		−0.00319 (−0.26)			
PMAX		−0.00175 (−0.41)			
PSTDEV		0.00394 (0.26)			
CONSTANT	−2.53 (−0.10)	−4.69 (−0.19)	−17.4 (−0.68)	20.6 (0.84)	11.0 (0.53)
REGIONAL DUMMIES	Yes	Yes	Yes	Yes	Yes
WEIGHTS	Country	Country	Country	Country	Country
R-SQUARED	0.793	0.785	0.799	0.832	0.792

Note: T-statistics are heteroscedasticity-consistent. Data are clustered at the level of the country. Note that * implies significance at the five % level of confidence and ** implies significance at the one % level of confidence.

or the one % level of confidence. The situation is similar in Northern Europe where the benefits range from 3.2% for Norway to 25.2% for Estonia. Unlike for Eastern Europe these welfare impacts are however not statistically significant even at the five % level of confidence. The situation of Northern Europe is very similar to that of Western Europe where welfare impacts range from 3.7% for France to 7.6% for Germany. The welfare impact for Southern Europe is more mixed. Impacts range from a 11.7% gain for Bosnia and Herzegovina to a 9.6% loss for Albania.

The largest impacts are felt in Africa where many countries' CS measures exceed their current GDPPC. In North Africa, losses range from 22.3% for Algeria to 48.8% for Egypt. These impacts moreover are statistically significant even at the one % level of confidence. Welfare losses increase as one moves to West Africa reaching 157.1% of GDPPC for Mali significant at the one % level of confidence. It seems appropriate to remind the reader that we are measuring losses using WTA rather than WTP. WTP to prevent the change would be smaller and necessarily less than GDPPC. Losses in Central, Eastern and Southern Africa are also large ranging from 19.6% for South Africa to 324.4% for Rwanda although the latter is not statistically significant at the five % level of confidence. Losses are smaller for Ethiopia due to its cooler climate and in the case of South Africa, due to its higher GDPPC.

In Western Asia and the Middle East impacts are also uniformly negative ranging from −2.0% in Turkey to −51.1% in Iraq, significant at the five and 1% respectively. In Southern and Central Asia by contrast the welfare impacts are more mixed ranging from a 10.3% gain for Kyrgyzstan to a 135.1 % loss for Bangladesh both significant at the one % level of confidence. In South East Asia the welfare impacts range from an equivalent GDPPC loss of 2.3% for Singapore to a 98.0% loss for Vietnam, the latter significant at 1%. In East Asia the welfare impact is small ranging from a loss of 5.9% for Hong Kong to a gain of 5.1% for South Korea. China registers a welfare gain of 4.5%.

The welfare impacts in Oceania are small and not statistically significant. The welfare impacts for South America are diverse ranging from a 9.6% GDPPC equivalent gain for Uruguay to a 93.0% loss for Brazil significant at 1% and 5% respectively. Welfare impacts in the Caribbean are negative for both Trinidad and Tobago and the Dominican Republic. Welfare impacts are also negative in Central America. The welfare impacts in North America range from a GDP equivalent loss of 35.6% for Mexico to a 7.5% gain for Canada although none of the estimates are statistically significant at the five % level of confidence.

Of the ten most populous countries (China, India, the United States, Indonesia, Brazil, Russia, Pakistan, Bangladesh, Japan and Nigeria) we find that six (India, Indonesia, Brazil, Pakistan, Bangladesh and Nigeria) are among the countries with the highest WTA as a percentage of GDPPC. But in terms of the ten highest emitters of CO_2 (China, the United States, India, Russia, Japan, Germany, Canada, the United Kingdom and South Korea), only India is adversely impacted by the direct impact of climate change. This does not bode well for any agreement significantly to reduce CO_2 emissions.

Notwithstanding the fact that the climate change scenario considered by Rehdanz and Maddison (2005) is somewhat different it is nevertheless possible to compare their findings with those contained in this study, at least for the 52 countries that the these two studies have in common. In the case of 11 countries both studies predict a positive welfare impact (Belarus, Russia, Ukraine, Estonia, Finland, Latvia, Lithuania, Norway, Sweden, Canada and South Korea). For 17 countries both studies predict a negative welfare impact (Italy, Macedonia, Spain, Ghana, Nigeria, Mexico, Argentina, Brazil, Colombia, Peru, Venezuela, Dominican Republic, Israel, Turkey, Bangladesh, India and the Philippines). For the remaining 38 countries the two welfare impacts are differently signed.

Using this information to construct a two-way contingency table suggests that the signs of the welfare impacts arising from the two studies are statistically independent (the Pearson chi-square statistic is

Table 5
The welfare impact of one climate change scenario.

Country	Change in DMs	Compensating surplus (PPP 2005 USD)	Percentage change
Eastern Europe			
Belarus	−41	3329	29.3**
Bulgaria	−8	742	6.5*
Czech Republic	−30	3244	13.9
Hungary	−5	598	3.3
Moldova	−11	449	16.2**
Poland	−29	3011	18.3
Romania	−4	405	3.4*
Russian Federation	−45	3783	25.7*
Slovakia	−16	1893	9.2
Ukraine	−17	1155	17.1**
Southern Europe			
Albania	7	−697	−9.6**
Bosnia and Herzegovina	−11	889	11.7**
Croatia	−5	540	3.1
Cyprus	4	−448	−1.7
Italy	3	−388	−1.3
Macedonia	9	−831	−9.4**
Slovenia	−10	1112	4.0
Spain	7	−836	−2.9
Northern Europe			
Estonia	−51	4734	25.2
Finland	−57	4713	14.0
Great Britain	−24	2551	7.4
Latvia	−42	3888	24.9*
Lithuania	−42	4070	23.1
Norway	−47	1583	3.2
Sweden	−41	3722	10.8
Western Europe			
France	−10	1136	3.7
Germany	−27	2579	7.6
Netherlands	−31	2847	7.4**
Switzerland	−28	2284	6.0
North Africa			
Algeria	15	−1649	−22.3**
Egypt	28	−2446	−48.8**
Morocco	15	−1315	−33.3**
West Africa			
Burkina Faso	54	−1400	−130.0**
Ghana	47	−1604	−118.7**
Mali	61	−1661	−157.1**
Nigeria	47	−1936	−99.8**
Central Eastern and Southern Africa			
Ethiopia	7	−268	−33.4*
Rwanda	52	−3078	−324.4
Uganda	53	−2633	−246.8*
South Africa	13	−1884	−19.6*
Tanzania	48	−1613	−134.3**
Zambia	48	−2595	−207.4*
North America			
Canada	−32	2696	7.5
United States of America	−2	135	0.3
Mexico	28	−4790	−35.6
South America			
Argentina	2	−231	−1.7*
Brazil	66	−8897	−93.0*
Chile	−5	662	4.9*
Colombia	33	−5207	−64.1*
Peru	46	−6522	−83.0*
Uruguay	−8	1132	9.6**
Venezuela	62	−7423	−63.1
Caribbean			
Dominican Republic	37	−3179	−42.3**
Trinidad and Tobago	25	−2629	−10.7
Central America			
El Salvador	53	−5167	−82.2**
Guatemala	48	−6085	−138.3*
Oceania			
Australia	8	−1070	−3.1
New Zealand	−8	1281	5.0
Western Asia and the Middle East			
Armenia	4	−233	−4.1**
Azerbaijan	10	−939	−11.6**
Georgia	6	−351	−7.7**
Iraq	31	−1622	−51.1**
Israel	13	−1747	−6.8
Jordan	14	−1146	−22.3**
Saudi Arabia	56	−5504	−25.3
Turkey	2	−244	−2.0*
South Central Asia			
Bangladesh	50	−1666	−135.1**
India	48	−2507	−89.6**
Iran	7	−656	−6.2*
Kyrgyzstan	−6	211	10.3**
Pakistan	47	−2265	−96.6**
East Asia			
China	−4	258	4.5**
Hong Kong	33	−2411	−5.9
Japan	−3	327	1.0
South Korea	−12	1315	5.1
South East Asia			
Indonesia	35	−2013	−54.5**
Malaysia	41	−4031	−30.7
Philippines	37	−1892	−58.3**
Singapore	35	−1144	−2.3
Thailand	48	−3573	−47.8*
Viet Nam	48	−2523	−98.0**

Source: See text. Note that * implies significance at the five % level of confidence and ** implies significance at the one % level of confidence. Note that these estimates refer to 2008 estimates for GDPPC.

2.35 with a probability of 0.125). If however the CS estimates of the respective studies are ranked for the countries in common Spearman's rank correlation coefficient is 0.306 with a probability of 0.027. This suggests that the magnitude of the welfare impacts is not entirely unrelated.

6. Conclusion

We confirm the results of earlier research suggesting that climate may have a significant impact on subjective wellbeing, but do so using what we believe to be a superior representation of the climate.

For those households inhabiting climates currently characterised by a large number of HDMs, our results indicate that warmer temperatures might improve SATISFACTION. But for those households inhabiting climates currently characterised by a large number of CDMs warmer temperatures might bring reduced SATISFACTION.

Our results do not provide a comprehensive assessment of the impact of climate change. We have considered only the direct impact of climate change on households and not the impact arising from changes in income or prices, or the direct impact arising from changes in climate elsewhere. The direct impact could nevertheless be a major component of the overall impact of climate change. Our analysis also picks up landscape effects if climate favours one type of landscape more than another (although it is not clear whether this is a strength or a weakness of the approach). Ours is also an equilibrium analysis that assumes households will have time perfectly to adapt themselves to future climates.

Future research should focus on analysing data on subjective wellbeing from smaller geographical areas. It would also be interesting to employ HDDs and CDDs derived from weather data rather than HDMs and CDMs derived from climate data. It is desirable to consider a wider range of climate variables than just temperature and precipitation. But above all it is essential that future researchers avoid presenting results based on specifications where the value of any change in climate is independent of baseline climate or which ignore seasonal variation.

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Appendix 1. Population weighted climate

Country	City	Weight
Albania	Tirana	1
Algeria	Algiers	0.698
	Oran	0.301
Andorra	Les Escaldes	1
Argentina	Buenos Aires	0.500
	Cordoba	0.268
	Rosario	0.230
Armenia	Yerevan	1
Australia	Sydney	0.451
	Melbourne	0.383
	Brisbane	0.164
Azerbaijan	Baku	1
Bangladesh	Dhaka	0.674
	Chittagong	0.325
Belarus	Minsk	0.778
	Gomel	0.221
Bosnia and Herzegovina	Sarajevo	1
Botswana	Gaborone	1
Brazil	Sao Paulo	0.557
	Rio de Janeiro	0.310
	Salvador	0.132
Bulgaria	Sofia	1
Burkina Faso	Ouagadougou	1
Canada	Toronto	0.474
	Montreal	0.328
	Vancouver	0.196
Chile	Santiago	1
China	Shanghai	0.457
	Beijing	0.361
	Tianjin	0.180
Colombia	Bogota	0.628
	Cali	0.199
	Medellin	0.171
Croatia	Zagreb	1
Cyprus	Nicosia	1
Czech Republic	Prague	1
Dominican Republic	Santo Domingo	1
Egypt	Cairo	0.741
	Alexandria	0.258
El Salvador	San Salvador	1
Estonia	Tallinn	1
Ethiopia	Addis Ababa	1
Finland	Helsinki	1
France	Paris	0.720
	Marseille	0.280
Georgia	Tbilisi	1
Germany	Berlin	0.661
	Hamburg	0.339

Appendix 1 (*continued*)

Country	City	Weight
Ghana	Accra	0.814
	Kumasi	0.185
Great Britain	London	0.871
	Glasgow	0.128
Guatemala	Guatemala	1
Hong Kong	Kowloon	1
Hungary	Budapest	1
India	Delhi	0.370
	Bombay	0.449
	Calcutta	0.179
Indonesia	Jakarta	0.475
	Surabaya	0.172
	Bandung	0.155
	Medan	0.125
	Semarang	0.071
Iran	Tehran	0.626
	Mashad	0.165
	Esfahan	0.110
	Tabriz	0.097
Iraq	Baghdad	0.763
	Mosul	0.236
Israel	Jerusalem	1
Italy	Rome	0.675
	Milan	0.324
Japan	Tokyo	0.429
	Osaka	0.570
Jordan	Amman	1
Kyrgyzstan	Bishkek	1
Latvia	Riga	1
Lithuania	Vilnius	1
Macedonia	Skopje	1
Malaysia	Kuala Lumpur	1
Maldives	Male	1
Mali	Bamako	1
Mexico	Mexico City	0.716
	Ecatepec	0.144
	Guadalajara	0.138
Moldova	Kishinev	1
Morocco	Casablanca	0.674
	Rabat-Sale	0.325
Netherlands	Amsterdam	1
New Zealand	Auckland	0.518
	Christchurch	0.481
Nigeria	Lagos	0.630
	Kano	0.369
Norway	Oslo	0.789
	Bergen	0.210
Pakistan	Karachi	0.618
	Lahore	0.381
Peru	Lima-Callao	0.818
	Arequipa	0.097
	Trujillo	0.084
Philippines	Manila	0.486
	Quezon City	0.513
Poland	Warsaw	1
Puerto Rico	San Juan	1
Romania	Bucharest	0.856
	Lasi	0.143
Russian Federation	Moscow	0.579
	St Petersburg	0.263
	Novosibirsk	0.080
	Nizhniy Novgorod	0.076
Rwanda	Kigali	1
Saudi Arabia	Riyadh	0.575
	Jedda	0.424
Serbia	Belgrade	1
Serbia and Montenegro	Podgorica	1
Singapore	Singapore	1
Slovakia	Bratislava	1
Slovenia	Ljubljana	1
South Africa	Cape Town	0.401
	Durban	0.352
	Johannesburg	0.246
	Seoul	1
Spain	Madrid	0.674
	Barcelona	0.325
Sweden	Stockholm	0.711

Appendix 1 (*continued*)

Country	City	Weight
	Gothenburg	0.288
Switzerland	Zurich	1
Taiwan	Taipei	1
Tanzania	Dar es Salaam	0.938
	Dodoma	0.061
Thailand	Bangkok	1
Trinidad and Tobago	Port-of-Spain	1
Turkey	Istanbul	0.718
	Ankara	0.281
Uganda	Kampala	1
Ukraine	Kiev	0.643
	Kharkiv	0.356
United States of America	New York	0.547
	Los Angeles	0.258
	Chicago	0.194
Uruguay	Montevideo	1
Venezuela	Caracas	0.484
	Maracaibo	0.515
Vietnam	Ho Chi Minh City	0.709
	Hanoi	0.290
Zambia	Lusaka	0.783
	Ndola	0.216
Zimbabwe	Harare	0.665
	Bulawayo	0.334

References

Becker, G., 1965. A theory of the allocation of time. The Economic Journal 75, 493–517.

Bradford, D.F., Hildebrandt, G.G., 1977. Observable preferences for public goods. Journal of Public Economics 8, 111–131.

Brereton, F., Clinch, J.P., Ferreira, S., 2008. Happiness, geography and the environment. Ecological Economics 65, 386–396.

Bruni, L., Porta, P.L. (Eds.), 2007. Handbook on the Economics of Happiness. Edward Elgar, Cheltenham, UK and Northampton, MA.

Cragg, M., Kahn, M., 1997. New estimates of climate demand: evidence from location choice. Journal of Urban Economics 42, 261–284.

Cushing, B., 1987. A note on specification of climate variables in models of population migration. Journal of Regional Science 27, 641–649.

Di Tella, R., MacCulloch, R.J., 2006. Some uses of happiness data in Economics. Journal of Economic Perspectives 20, 25–46.

Dubin, J., McFadden, D., 1984. An econometric analysis of residential electric appliance holdings and consumption. Econometrica 52, 345–362.

Ferreira, S., Moro, M., 2010. On the use of subjective well-being data for environmental valuation. Environmental and Resource Economics 46, 249–273.

Frey, B., 2008. Happiness: A Revolution in Economics. MIT Press, Cambridge, MA.

Frijters, P., Van Praag, B., 1998. The effects of climate on welfare and wellbeing in Russia. Climatic Change 39, 61–81.

Lawrence, A., Aigner, D., 1979. Modelling and forecasting time-of-day and seasonal electricity demands. Journal of Econometrics 9, 1–237.

Layard, R., 2005. Happiness: Lessons from a New Science. Penguin, New York.

Luechinger, S., 2009. Valuing air quality using the life satisfaction approach. The Economic Journal 119, 482–515.

Maddison, D., 2001a. The amenity value of the climate of Britain. In: Maddison, D. (Ed.), The Amenity Value of the Global Climate. Earthscan, London.

Maddison, D., 2001b. The amenity value of the climate: the household production function technique. In: Maddison, D. (Ed.), The Amenity Value of the Global Climate. Earthscan, London.

Maddison, D., 2003. The amenity value of climate: the household production function approach. Resource and Energy Economics 25, 155–175.

Maddison, D., Bigano, A., 2003. The amenity value of the Italian climate. Journal of Environmental Economics and Management 45, 319–332.

Mendelsohn, R., 2001. A hedonic study of the non-market impacts of global warming in the US. In: Maddison, D. (Ed.), The Amenity Value of the Global Climate. Earthscan, London.

Mueller, V., 2005. Valuing climate amenities in Brazil using a hedonic pricing framework. PhD dissertation submitted to the Faculty of the Graduate School of the University of Maryland.

Nordhaus, W., 1996. Climate amenities and global warming. In: Nakicenovic, N., Nordhaus, W., Richels, R., Toth, F. (Eds.), Climate Change: Integrating Science, Economics and Policy. IIASA, Laxenburg.

Nordhaus, W., 2008. A Question of Balance — Weighing the Options on Global Warming Policies. Yale University Press, New Haven.

Parker, P., 1995. Climatic Effects on Individual, Social and Economic Behaviour: A Physioeconomic Review of Research across Disciplines. Greenwood Press, Westport, CT.

Pearce, E., Smith, C., 1993. The World Weather Guide. Helicon, Oxford.

Rehdanz, K., Maddison, D., 2005. Climate and happiness. Ecological Economics 52, 111–125.

Rehdanz, K., Maddison, D., 2009. The amenity value of climate to German households. Oxford Economic Papers 61, 150–167.

Stern, N., Peters, S., Bakhshi, V., Bowen, A., Cameron, C., Catovsky, S., Crane, D., Cruickshank, S., Dietz, S., Edmonson, N., Garbett, S.-L., Hamid, L., Hoffman, G., Ingram, D., Jones, B., Patmore, N., Radcliffe, H., Sathiyarajah, R., Stock, M., Taylor, C., Vernon, T., Wanjie, H., Zenghelis, D., 2006. Stern Review: The Economics of Climate Change. HM Treasury, London.

Stutzer, A., Frey, B., 2010. Recent advances in the economics of Individual subjective well-being. Social Research 77, 679–714.

Thom, H., 1954. The rational relationship between heating degree days and temperature. Monthly Weather Review 82, 1–6.

Tol, R.S.J., 2009. The economic effects of climate change. Journal of Economic Perspectives 23, 29–51.

Van der Vliert, E., Huang, X., Parker, P., 2004. Do hotter and colder climates make societies more, but poorer societies less, happy and altruistic? Journal of Environmental Psychology 24, 17–30.

Van Praag, B.M.S., 1988. Climate equivalence scales: an application of a general method. European Economic Review 32, 1019–1024.

Van Praag, B.M.S., Baarsma, B.E., 2005. Using happiness surveys to value intangibles: the case of airport noise. The Economic Journal 115, 224–246.

Van Praag, B.M.S., Ferrer-i-Carbonell, A., 2004. Happiness Quantified — A Satisfaction Calculus Approach. Oxford University Press, Oxford.

Welsch, H., 2002. Preferences over prosperity and pollution: environmental valuation based on happiness surveys. Kyklos 55, 473–494.

Welsch, H., 2006. Environment and happiness: valuation of air pollution using life-satisfaction data. Ecological Economics 58, 801–813.