Climate Change Economics, Vol. 4, No. 1 (2013) 1350004 (21 pages)

DOI: 10.1142/S2010007813500048

DO GEOGRAPHICAL VARIATIONS IN CLIMATE INFLUENCE LIFE-SATISFACTION?

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Published 20 March 2013

Accounting for socioeconomic and demographic variables, as well as country-specific effects, households' marginal willingness to pay for climate is revealed using European data on life-satisfaction. Individuals located in areas with lower average levels of sunshine and higher average levels of relative humidity are less satisfied as are individuals in locations subject to significant seasonal variation in monthly mean temperatures and rain days. Ranking regions by climate households appear strongly to favor the Mediterranean climate over the climate of Northern Europe.

Keywords: Life-satisfaction; Europe; willingness to pay; climate; climate change.

JEL Codes: C21, I31, Q51, Q54

1. Introduction

Starting with Nordhaus (1993), numerous researchers have presented benefit-cost analyses of global GHG emissions targets. But little attention has been paid to certain types of impact and, in particular, to the direct value to households of changes in the climate.

To understand better the direct value of climate to households, a number of studies have made reference to the Household Production Function (HPF) theory (Becker, 1965). According to the HPF theory, households do not consume marketed commodities but instead combine these with nonmarket goods using household production technologies. It is the resulting service flows that are of direct value to the household.

The importance of climate in the production of service flows explains why households inhabiting different climates enjoy different levels of well-being. It is

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because of differences in the cost of generating service flows. The HPF framework also explains why households exhibit different expenditure patterns. Households substitute inputs whilst economizing on the consumption of costly service flows.

Although it is logical to enquire about the cost of particular climates in terms of additional expenditures, estimating the direct value of climate change on households is difficult. This is because climate is an input in the production of many service flows, none of which are directly observable. Many researchers therefore regard the HPF concept as a purely heuristic device and have consequently favored alternative valuation techniques.

This paper analyzes the preferences of European households for particular climates. Although these preferences arise because of the role of climate in producing service flows, our approach involves neither estimating household production functions nor the demand for unobservable service flows. Instead, our strategy involves examining how households inhabiting different climates differ in terms of reported life-satisfaction.

Previous studies have used reported life-satisfaction or similar to analyze households' preferences for climate using cross-country data (e.g., Van der Vliert *et al.*, 2004; Rehdanz and Maddison, 2005). These papers average the climates of major population centers. Country-specific studies, by contrast, may contain insufficient variation in the variables of interest.

This paper overcomes the limitations of existing research using data on life-satisfaction from the 1999/2000 third wave of the European Values Survey (EVS). This data contains observations from 24 European countries at the NUTS level.[1] NUTS regions possess homogeneous climates, thereby avoiding the need for averaging procedures. Furthermore the dataset includes observations from the Arctic Ocean to the Mediterranean Sea, thus guaranteeing significant variation in climate.

The remainder of the paper is structured as follows. Section 2 reviews other researchers' attempts to estimate the value of climate to households and explains the life-satisfaction approach to environmental valuation. Section 3 presents an empirical model and describes the data. Section 4 econometrically analyzes the impact of climate on life-satisfaction. Section 5 estimates marginal willingness to pay for climate and presents an index of regions' climates. Section 6 provides the conclusion.

2. Literature Review

In assessing the direct impact of climate change on households, the key question is what is the maximum that a household would be willing to pay (WTP) for moving to a

[1]NUTS is a classification system for dividing up the EU into regional territories. NUTS1 are regions with populations between 3 and 7 million. NUTS2 are subdivisions of NUTS1 with populations between 0.8 and 3 million. NUTS3 are the smallest regions with populations between 0.15 and 0.8 million. Our dataset contains 38 NUTS1 regions, 89 NUTS2 regions and 82 NUTS3 regions.

superior climate or alternatively, what is the minimum that the household would be willing to accept (WTA) as compensation for an inferior climate.

A variety of techniques exist to estimate the value of climate to households. These techniques use spatial variation in climate as an analog for climate change. They address the key issue of adaptation by comparing households that have already perfectly adapted to the climate.

The direct impact of climate change on households does not constitute a complete account of the socioeconomic impacts of climate change. Climate change might also affect incomes and consumer prices. In addition, households may have preferences over the climates of other locations. Below, we describe five alternative approaches to monetary valuation.

Hedonic theory suggests that the costs and benefits associated with nonmarket goods like climate are capitalized into property prices and wage rates. Migration induced changes in house prices and wage rates eliminate the net benefits of different locations (Roback, 1982).

For studies undertaken in the US, see Hoch and Drake (1974), Englin (1996) and Albouy (2008). For those undertaken elsewhere, see Maddison and Bigano (2003), Srinivasan and Stewart (2004) and Rehdanz and Maddison (2009). Some studies look for compensating differentials in either the housing market (Englin, 1996) or the labor market (Hoch and Drake, 1974).

The technique has significant limitations with respect to valuing the climate. Rehdanz and Maddison (2009) argue that, over large geographical distances, the assumption of a unified market for housing and labor becomes untenable.

Determining the value of environmental goods using the HPF approach involves specifying an indirect utility function including income, prices and nonmarket goods as arguments. The associated Marshallian demand functions are estimated on household expenditure data.

Unlike the hedonic technique, one need not assume that the household is in hedonic equilibrium. The weakness of the approach is the assumption of demand dependency. Examples of the household production function approach applied to climate include Maddison (2003) and Maddison *et al.* (2011).

Hypothetical equivalence scales involve asking survey respondents to report the minimum income for their household to reach a specified level of utility. Van Praag (1988) and Frijters and Van Praag (1998) apply this technique to Europe and Russia, respectively. It is necessary to assume that households share an identical understanding of a verbally defined standard of living.

The random utility model assumes that households choose from a set of locations characterized by different prices, incomes and nonmarket goods. In moving to preferred locations, households reveal their preferences. WTP for climate is found by calculating the income required as compensation (see Cragg and Kahn, 1997; Bayer *et al.*, 2009). It is boldly assumed there is no cost to migration.

Recently, economists have begun to use survey data on subjective well-being to value nonmarket goods.[2] Survey respondents are confronted with questions such as

How satisfied are you with your life on a 1 *to* 10 *scale where* 1 *means completely dissatisfied and* 10 *means completely satisfied*?

Alternatively, the question might refer to happiness. Interpreting the response as a measure of the utility of the respondent requires that respondents are able accurately to map their true utility onto a discrete integer scale

$$s_i = g_i(u_i)$$

where s_i is the reported satisfaction of individual i and g_i describes the monotonic function used by individual i to convert utility u_i to satisfaction. In order to compare survey responses from more than one individual, it is necessary further to assume that all respondents use a common function g to convert utility to life-satisfaction

$$g_i = g \forall i$$

The relationship g between satisfaction and utility raises the question how one should analyze reported life-satisfaction. Given that g is unknown, it may be prudent to assume an ordinal association. If an individual reports a value of 8, we should merely assume that they are more satisfied than if they reported 7. By contrast, if g were a linear function, then it would be possible to estimate respondents' utility functions with OLS.

Ferrer-i-Carbonell and Frijters (2004) find that assuming satisfaction to be a linear function does not make any significant difference. Specifying

$$s = g(u(p, y, z))$$

the *MWTP* for the nonmarket good is given by

$$MWTP = \frac{\partial g(u)/\partial u \times \partial u/\partial z}{\partial g(u)/\partial u \times \partial u/\partial y} = \frac{\partial u/\partial z}{\partial u/\partial y}$$

The subjective well-being approach is a potentially powerful tool to estimate the value of climate to households.

Van der Vliert *et al.* (2004) examine how temperature and temperature-squared affect nationally averaged measures of subjective well-being. For large countries, temperature data was averaged over major population centers. For poor countries, the paper points to an inverted U-shaped relationship between subjective well-being and temperature (reversed for rich countries). Fischer and Van der Vliert (2009) consider the effect of climate on general health, burnout, anxiety and depression.

[2]Easterlin (1974) conducted the first empirical economic analysis of subjective well-being. A large literature now links subjective well-being to economic indicators (Frey and Stutzer, 2002). For a review of the literature focusing on environmental aspects, see Welsch and Kühling (2009).

Rehdanz and Maddison (2005) conduct a cross-country study for 67 countries between 1972 and 2000. They find that society prefers a climate characterized by cooler temperatures in the hottest month, and warmer temperatures in the coolest month.

In their study of Ireland, Brereton *et al.* (2008), Moro *et al.* (2008) and Ferreira and Moro (2010) use a GIS approach, providing highly detailed information on households' immediate surroundings. Brereton *et al.* (2008) find annual average wind speed negatively impacts life-satisfaction, whereas higher January minimum night-time temperatures and higher July maximum daytime temperatures increase it. Moro *et al.* (2008) use their results to rank regions in Ireland according to their quality of life (QOL). Ferreira and Moro (2010) also find a positive coefficient for January minimum night-time temperatures.

Compared to other techniques, the subjective well-being approach possesses certain advantages. It avoids a range of assumptions concerning the functioning of markets associated with the hedonic technique and a range of assumptions concerning the structure of preferences associated with the HPF technique. It also avoids asking individuals about hypothetical changes, e.g., "How much are you willing to pay to enjoy the climate of Nice?" It may succeed in valuing changes in environmental quality even when the respondent is not conscious of their impact. On the other hand, the subjective well-being approach assumes that respondents use a common function to convert utility to a measure of social well-being. It is essential that the marginal change in social well-being arising from a marginal change in income is measured accurately. For a further discussion of the subjective well-being approach to valuation, see Welsch (2009) and Welsch and Kühling (2009).

3. Model Specification and Data Sources

The goal of this paper is to isolate the effect of climate variables on life-satisfaction, whilst controlling for a range of other factors. The basic model employed for this purpose is

$$s_i = \alpha + \sum_j \gamma_j H_{ji} + \sum_k \delta_k G_{ki} + \sum_m \phi_m Z_{mi} + \varepsilon_i$$

where s_i is the reported life-satisfaction of individual i measured on an integer scale, H represents socioeconomic and demographic characteristics, G represents geographical variables (including country dummies but excluding climate variables) and Z represents climate variables. The symbol ε represents an error term and γ_j, δ_k and δ_m are parameters. Based on the results by Ferrer-i-Carbonell and Frijters (2004), we begin our empirical analysis using OLS.[3]

[3]Using OLS also enables us to tackle the problem of errors in variables using standard econometric techniques.

Data on reported life-satisfaction are taken from the 1999–2000 third wave of the EVS.[4] For our purposes, the key question, translated by country-specific research agencies, is

All things considered, how satisfied are you with your life as a whole these days?

Respondents were invited to give a response between 1 and 10 where 1 is "entirely dissatisfied" and 10 "completely satisfied".

Turning now to the or similar socioeconomic and demographic variables, we include the logarithm of net household income. We also include the squared value of the logarithm of household income to improve the fit.

To capture the U-shaped relationship between age and subjective well-being, we include both age and age squared. Gender is included to account for the possibility that females are happier than males. Dummy variables identify whether the respondent is the head of the household and an EU citizen. A dummy variable denotes religious beliefs. Even though health status is likely to be important the 1999–2000 EVS does not include any questions on health status.

We include the number of individuals present in the household identifying four different age categories (<5, 5–12, 13–17 and >18). Eight dummy variables identify the employment status of the respondent (full-time, part-time, self-employed, retired, housewife, student, unemployed and other).

Dummies identify those who are married, living together, single, divorced, separated or widowed. Dummies for educational attainment include not finished primary school, finished primary education, incomplete secondary education, completed secondary education, incomplete higher education and finished university degree. We also include the age the respondent finished their education (their current age if still in education).

A set of dummy variables categorizes observations by settlement size (varying from <2000 to 500,000+). Elevation controls for topographical features. A dummy identifies NUTS regions bordering the sea. Latitude is included to capture the variation in hours of daylight. Longitude is included to control for the fact that daylight arrives later in the West of any given time zone.

Data on population density is taken from the EUROSTAT website. Lastly, a set of country dummies is included accounting for differences in prices, political systems, culture and general differences in the way in which the question on life-satisfaction is perceived.

Turning finally to climate variables, we obtain gridded climate data for the period 1961–1990 from New *et al.* (2002). This is aggregated to NUTS regions. The data include monthly averages for temperature, precipitation, frost days, relative humidity, rain days, percentage of possible sunshine and wind speed. The highest correlation is observed for average annual temperature and frost days (-0.947).

[4]Available online at http://www.europeanvaluesstudy.eu/evs/surveys/survey-1999-2000.html. Note that life-satisfaction is the only measure of social well-being contained in the EVS dataset.

We note several problems. All questions on household income were answered in national currencies. These currencies were then converted into Euros.[5] Respondents were not required to reveal exact figures for net household income, only to identify an income decile. We take the midpoint. For example, a net household income range between €20,000 and €25,000 was interpreted as €22,500. We address the problem of measurement error below.

Comprehensive climate data for Iceland is not available. Data on net household income is not available for Finland, Romania, Poland and Hungary. Data on the number of over-18s present in the household was not available for Greece, and we replace the missing values for the number of over-18s with the sample average. In total, the data consist of slightly in excess of 17,500 observations, across 209 NUTS regions, in 19 different countries. Summary statistics are available as supplementary materials.

4. Results

Regression results from seven different models are contained in Table 1. These models are characterized by different estimation techniques and specifications of the climate. We begin by discussing the results from Model 1. Throughout, we report robust T-statistics, which assume clustering at the level of the NUTS region.

The logarithm of net household income is positive, whilst the square of the logarithm of net household income is negative. Both are significant at the 1% level, confirming the importance of net household income.

Being a citizen of the country in which one is resident has a positive effect on life-satisfaction and is significant at the 1% level of significance. Consistent with earlier studies, the coefficients on age and age squared are respectively negative and positive. Life-satisfaction is at a minimum around middle age.

The coefficient for religion is positive and significant at the 1% level of significance. Males appear to be less satisfied with their lives. The number of children does not have a statistically significant effect and neither does the number of people in each different age category.

Being the head of the household has no statistically significant impact. Individuals who live with their parents are similar to those who do not in terms of their life-satisfaction. Married people are more satisfied with their lives than those who are single. Those who are divorced, separated or widowed are less satisfied. People who are living together are no different from those who are single.

Unemployment has a large and negative impact on satisfaction. By contrast, those who are self-employed or retired both report higher life-satisfaction. Those who have obtained a University degree enjoy the greatest life-satisfaction. The variables

[5] Currencies were converted to Euros using exchange rates prevailing when the surveys were conducted.

Table 1. Regression results.

Variable	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 OLS	Model 5 ordered logit	Model 6 IV	Model 7 OLS
Log net household income (€)	1.855625***	1.846406***	1.831099***	1.824506***	1.493714***	4.087619***	2.046224***
Log net household income squared (€)	−0.0758998***	−0.0755806***	−0.07475***	−0.0744212***	−0.0597922***	−0.1919657**	−0.074129***
Log difference in household income							−0.2362405
Citizen	0.3235857***	0.320691***	0.3209257***	0.3179906***	0.2308307***	0.3238825***	0.3205656***
Age	−0.0727415***	−0.0727479***	−0.073456***	−0.0734476***	−0.0646489***	−0.0733273***	−0.0734627***
Age-squared	0.0006883***	0.0006888***	0.0006924***	0.0006938***	0.0006113***	0.0006912***	0.0006924***
Number of children	0.0179828	0.0178022	0.0188476	0.017929	0.0143382	0.0186397	0.0189863
Are you head of household?	0.0226402	0.0196414	0.0229801	0.0219365	0.0009777	0.0220074	0.0225784
Are you religious?	0.1062832***	0.1004003***	0.1093013***	0.1065997***	0.1025496***	0.1074256***	0.1074072***
Number children 18+	−0.0232059	−0.0206208	−0.0215194	−0.0202596	−0.0199125	−0.0209469	−0.020737
Number children 13–17	−0.014197	−0.014816	−0.0139005	−0.0139734	−0.0223342	−0.0132414	−0.0137526
Number children 5–12	−0.0385389	−0.0392505	−0.0395657	−0.0400139	−0.0385437	−0.0389712	−0.0392661
Number of children <5	0.0143537	0.0139301	0.0141514	0.0141176	−0.0029032	0.0156208	0.0147454
Do you live with your parents?	−0.1032898	−0.1094791	−0.1017784	−0.1046362	−0.0742467	−0.1027	−0.1023003
Are you male? (1 = Yes)	−0.0732726*	−0.0724939*	−0.0730164*	−0.0729724*	−0.0698544**	−0.0719614*	−0.0725073*
Age finished education	0.0223429	0.0204999	0.0172571	0.0164628	0.0128753	0.016619	0.0174364
Age finished education squared	−0.0003157	−0.0002848	−0.0002218	−0.0002129	−0.0002317	−0.0002134	−0.0002261
Married	0.3702062***	0.3717723***	0.3760254***	0.3774512***	0.3453115***	0.3769915***	0.3763282***
Living together	0.0604787	0.0433278	0.0430146	0.0349104	−0.0483126	0.0423706	0.0428625

Table 1. (*Continued*)

Variable	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 OLS	Model 5 ordered logit	Model 6 IV	Model 7 OLS
Divorced	−0.1710892**	−0.1660419**	−0.1666583**	−0.1633042**	−0.1355669**	−0.1692233**	−0.1666545**
Separated	−0.5935067***	−0.5949659***	−0.5960403***	−0.5939918***	−0.469995***	−0.5951064***	−0.5968084***
Widowed	−0.1871124**	−0.1816164**	−0.1853174**	−0.1800282**	−0.1594085**	−0.1863668**	−0.1866457**
Full-time working	0.2546977*	0.2607956*	0.2568565*	0.2576518*	0.1321309	0.2570637*	0.2591815*
Part-time working	0.2246654	0.2343785	0.2290126	0.2317772	0.0927899	0.2276384	0.2288452
Self-employed	0.3657712**	0.37145**	0.3679186**	0.367163**	0.2225918	0.3677078**	0.3704655**
Retired	0.3490392**	0.3533194**	0.3540532**	0.3516963**	0.281682**	0.3529572**	0.3555222**
Housewife	0.2367635	0.2412856	0.2404917	0.2423687	0.1538906	0.2375374	0.2424918
Student	0.2906298*	0.3060839*	0.2919284*	0.2984246*	0.1477291	0.2951203*	0.2947534*
Unemployed	−0.7237268***	−0.7170088***	−0.720327***	−0.7184927***	−0.6668934***	−0.7176768***	−0.7173757***
Education level 1 (lowest)	−0.3260271**	−0.3335181**	−0.3372334**	−0.3438946**	−0.3218205**	−0.3375601**	−0.337703**
Education level 2	−0.2842646***	−0.2956985***	−0.2955142***	−0.3031151***	−0.2660081***	−0.296889***	−0.2975559***
Education level 3	−0.2404874**	−0.2478674***	−0.251198***	−0.2563885***	−0.2234029***	−0.2512222***	−0.251047***
Education level 4	−0.240136***	−0.2439317***	−0.2440943***	−0.2482547***	−0.2237435***	−0.2469948***	−0.2470201***
Education level 5	−0.2063999**	−0.210602**	−0.218049**	−0.2201942**	−0.1819952**	−0.2177034**	−0.2193079**
Education level 6	−0.1459005**	−0.1510944**	−0.1544166**	−0.1576375**	−0.1318581**	−0.1533889**	−0.1545939**
Education level 7	−0.0990984	−0.1045809	−0.1056099	−0.1105388	−0.0752844	−0.1044994	−0.1053217
Latitude (°)	0.0458342	0.049926	0.0476773	0.041471	0.0459814	0.0480563	0.0371971
Longitude (°)	−0.0301983**	−0.0215153*	−0.0087455	0.0001144	−0.0088083	−0.0134167	−0.0070927
Coastline	−0.1388125*	−0.1254454	−0.1570126**	−0.1624362**	−0.1245485*	−0.1829266**	−0.163804**
Population density (per km^2)	−0.0000895***	−0.0000936***	−0.0001088***	−0.0000996***	−0.0001032***	−0.0001085***	−0.0001078***
Elevation (km)	0.1247077	0.0159717	−0.5476876	−0.5915534	−0.4846422	−0.4993421	−0.6389077
Size <2000	0.0659828	0.0543906	0.0596377	0.0529705	0.0644363	0.062533	0.0627696

Table 1. (*Continued*)

Variable	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 OLS	Model 5 ordered logit	Model 6 IV	Model 7 OLS
Size 2000–5000	0.0220486	0.0212471	0.026916	0.0263113	0.0097197	0.0221255	0.0265562
Size 5000–10,000	0.139886	0.1293143	0.1396166	0.1368066	0.1380862*	0.1352441	0.1339072
Size 20,000–50,000	0.0343953	0.0283719	0.0221698	0.0227634	0.0195254	0.0204576	0.0223424
Size 50,000–100,000	−0.0718612	−0.0684992	−0.074417	−0.0710396	−0.0698194	−0.07195	−0.0734738
Size 100,000–500,000	−0.0519341	−0.0619322	−0.0434402	−0.050196	−0.0422233	−0.060238	−0.0515832
Size 500,000+	0.0669042	0.0562634	0.084141	0.0702444	0.0551996	0.0545706	0.0616239
Average annual temperature (°C)	0.0149282	0.2641135	−0.0136167	0.0344868	−0.0018669	0.0163297	−0.0231531
Average annual relative humidity (%)	−0.0201267	−0.1283909	−0.0467358***	−0.3307896*	−0.0393301**	−0.0369813**	−0.0445171**
Average annual percentage sunshine (%)	0.0117317	0.0526692	0.0356521***	0.0668563	0.0343523***	0.0366921***	0.0384529***
Average annual wind speed (km/hr)	−0.021707	−0.2037298	−0.1263797	−0.3981965	−0.1112643	−0.1425713	−0.1215321
Total rain days	0.0003625	−0.0305926***	0.0044009	−0.0076393	0.0036379	0.0048367	0.0049458
Total frost days	−0.0004801	−0.0091796	0.0039451	0.0049096	0.0054185	0.0048124	0.004214
Total precipitation (mm)	0.0001053	0.0000337	−0.0000871	−0.0004625	−0.0001347	−0.0000613	−0.0000738
Average annual temperature squared (°C)		−0.014558*		−0.003457			
Average annual relative humidity squared (%)		0.0006635		0.001867			
Average annual percentage sunshine squared (%)		−0.0003338		−0.0004269			
Average annual wind speed squared (km/hr)		0.0201604		0.0339243			
Total rain days squared		0.0001063***		0.000037			

Table 1. (*Continued*)

Variable	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 OLS	Model 5 ordered logit	Model 6 IV	Model 7 OLS
Total frost days squared		0.0000424		6.10e-07			
Total precipitation squared (mm)		−2.38e-08		1.53e−07			
Standard deviation average annual temperature (°C)			−0.4198457***	−0.4161345**	−0.4006336***	−0.3364966**	−0.3998023***
Standard deviation average annual relative humidity (%)			0.0093058	0.0105146	0.0099821	−0.0015291	0.0084084
Standard deviation average annual per cent sunshine (%)			0.002436	−0.0011376	0.0045774	0.0066802	0.0035506
Standard deviation average annual wind speed (km/hr)			0.3130407	0.2965248	0.3530553	0.4694543 (1.35)	0.4050041 (1.16)
Standard deviation total rain days			−0.226752***	−0.1826252**	−0.1719488***	−0.2250001***	−0.2159266***
Standard deviation total frost days			0.008418	−0.0197899	0.0058146	−0.0075391	0.0037423
Standard deviation total precipitation (mm)			0.0001803	0.0020849	−0.0007382	−0.0002357	0.0005176
Predicted residuals log household income						−2.369064*	
Predicted residuals log household income squared						0.1229535	
Constant	−4.097704	1.431863	0.028259	12.31019		−11.48241	−1.053192

Table 1. (*Continued*)

Variable	Model 1 OLS	Model 2 OLS	Model 3 OLS	Model 4 OLS	Model 5 ordered logit	Model 6 IV	Model 7 OLS
Country dummies?	YES	YES	YES	YES	YES	YES	YES
Observations	17,923	17,923	17,923	17,923	17,923	17,923	17,923
R^2	0.2200	0.2210	0.2218	0.2222		0.2222	0.2220
Pseudo R^2					0.0569		
AIC	4.233	4.233	4.232	4.232		4.232	4.232
BIC	−99,042.710	−98,997.508	−99,016.007	−98,956.857		−99,005.260	−99,009.653
Joint significance test of climate variables	$F(7, 208) = 0.53$ Prob $> F = 0.8135$	$F(14, 208) = 1.54$ Prob $> F = 0.1002$	$F(14, 208) = 2.80$ Prob $> F = 0.0008$				
Joint significance test of squared climate variables				$F(7, 208) = 1.30$ Prob $> F = 0.2501$			
Joint significance test predicted residuals						$F(2, 208) = 1.71$ Prob $> F = 0.1827$	

Source: See text. *** means significant at the 1% level of significance, ** means significant at the 5% level of significance and * means significant at the 10% level of significance.

describing the age the respondent finished education and its squared value are not significant.

Turning to geographical variables, the coastline dummy is negative but significant at the 10% level. Population density is negative and significant at the 1% level. Although this variable may capture the disamenities associated with urban living, paradoxically the size of settlement variables are all insignificant. Whilst latitude has no significant impact, longitude is negative and significant at the 5% level. Elevation has no significant impact.

None of the climate variables (annual averages for temperature, relative humidity, percentage sunshine, wind speed as well as annual totals for rain days, frost days and precipitation) are individually significant even at the 10% level. A joint F-test on the slopes of the climate variables is insignificant.

Model 2 adds quadratic terms for all climate variables. We include these to determine whether climate preferences depend on the baseline climate, e.g., Maddison and Bigano (2003). There are no changes in the coefficients of the nonclimate variables or their significance, and we do not discuss them. Total rain days and its squared value are now significant at the 1% level. However, the joint F-test for the climate variables and their squares remains insignificant at the 10% level.

Model 3 drops the squared terms and replaces them with the standard deviation of the monthly values for each of the seven climate variables.[6] These are included to investigate whether individuals have preferences for variation over the annual cycle (Englin, 1996). The standard deviation σ_T of monthly mean temperature T is given by

$$\sigma_T = \sqrt{\frac{(T_{\mathrm{JAN}} - \overline{T})^2 + (T_{\mathrm{FEB}} - \overline{T})^2 + \cdots + (T_{\mathrm{DEC}} - \overline{T})^2}{12}}$$

The R-squared value improves in relation to Model 2. The inclusion of standard deviations has a profound effect on the perceived importance of the climate variables which are now jointly significant at one percent. Separate group significance tests for the annual values of climate variables and standard deviations are also significant at the one percent level.

Higher relative humidity has a negative effect on life-satisfaction, whilst sunshine improves life-satisfaction. Both are individually significant at the 1% level. Large standard deviations in monthly mean temperatures and the number of rain days reduce life-satisfaction and are statistically significant at the 1% level.

Given the apparent importance of standard deviations, Model 4 reinstates the squared terms but they remain jointly insignificant even at the 10% level of significance.

[6]This model has a better fit than an alternative regression including January and July averages of climate variables (results not shown). We also experimented with two indices used in Van de Vliert (2009), specifically those based on absolute deviations from 22°C for the average highest and lowest temperatures in the coldest month, and for the average highest and lowest temperatures in the hottest month. When these are included in Model 1, they are jointly significant at the 1% level. However, when they are included in Model 3, which already includes standard deviations of all the climate variables, these variables are not significant even at the 10% level.

To assess the robustness of our results, we ran an additional regression for Model 3 excluding the geographically larger NUTS1 regions from the sample. Average relative humidity, average sunshine, the standard deviation of temperature and the standard deviation of rain days remain statistically significant, with their coefficients virtually unchanged. We investigated the effect of interacting climate variables contained in Model 3 with income levels. As a group, these interacted terms are, however, statistically insignificant.

So far it has been assumed that OLS is a suitable estimator for life-satisfaction. Using the Ordered Logit estimator, Model 5 assumes an ordinal relationship between utility and life-satisfaction. This generates only very small changes to the coefficients reported for Model 3. The absence of any major differences implies that OLS is a suitable estimator.

Model 6 estimates Model 3 again using instrumental variables (IVs) to deal with possible errors in the measurement of net household income. These might arise because net household income is reported only in terms of income deciles. IVs deal with measurement error by finding a variable which is correlated with actual income but not with the measurement error.

Constructing suitable IVs is straightforward in a panel study where lagged values of net household income may suffice (Oswald and Powdthavee, 2008). Such an approach is not possible in a cross sectional dataset. Our IVs are the logarithm of average net household income of all other survey respondents belonging to the same NUTS region, and the logarithm of average net household income of all other survey respondents belonging to the same NUTS region squared.

We evaluate the IVs by means of a Durbin–Wu–Hausman test (Davidson and MacKinnon, 1993). This test involves obtaining residuals from an auxiliary regression of the IVs against the variables potentially afflicted by measurement error. The residuals from the auxiliary regressions are then added as additional explanatory variables into the main OLS regression. A joint test of significance of the residuals is statistically insignificant at the 10% level. This confirms that any measurement error associated with net household income does not significantly impact on the results.

Easterlin (1974) comments that subjective well-being might depend on individuals' reference income. Whilst some researchers (e.g., Layard *et al.*, 2009) find evidence that reference income is important others do not (e.g., Stevenson and Wolfers, 2008). In order to test for the importance of reference income, we include in Model 7 the difference between net household income and average net household income for the NUTS region. This variable is statistically insignificant at the 10% level.

5. Discussion

One of our objectives is to measure, in monetary terms, European households' preferences for particular types of climate. Our approach however, also permits

Table 2. Marginal willingness to pay for climate variables.

Climate variable	Coefficient	MWTP/€	95 percent confidence interval
Average Relative Humidity	−0.0467358	−1927.75***	−468.91, −3386.59
Average Sunshine	0.0356521	1470.57***	370.45, 2570.70
Average Temperature	−0.0136167	−561.66	−8424.90, 7301.58
Average Wind Speed	−0.1263797	−5212.89	−12408.20, 1982.37
Total Rain Days	0.0044009	181.52	−112.52, 475.57
Total Frost Days	0.0039451	162.72	−162.73, 488.18
Total Precipitation	−0.0000871	−3.59	−20.36, 13.17
Temperature Std Dev	−0.4198457	−17317.70***	−29227.50, −5408.00
Relative Humidity Std Dev	0.0093058	383.84	−2043.04, 2810.73
Sunshine Std Dev	0.002436	100.47	−1868.92, 2069.89
Wind Speed Std Dev	0.3130407	12912.27	−14898.80, 40723.30
Rain Days Std Dev	−0.226752	−9353.04***	−14993.60, −3712.44
Frost Days Std Dev	0.008418	347.22	−2488.44, 3182.89
Precipitation Std Dev	0.0001803	7.43	−478.45, 493.32

Source: See text. *** means significant at 1% level of significance, ** means significant at 5% level of significance and * means significant at the 10% level of significance.

us to describe preferences for climate directly in terms of utility. Depending on the audience nonmonetary measures of households' preferences may find greater acceptability.

Table 2 presents household *MWTP* for climate variables. *MWTP* is calculated by dividing the marginal utility of each climate variable by the marginal utility of money. Due to the inclusion of the logarithm of net household income (as well as the squared value of the logarithm of net household income), *MWTP* for climate variables depends on household net income. We evaluate *MWTP* at the sample mean for net household income (€15,880.70). *MWTP* is calculated as follows

$$MWTP_i = \frac{\phi_i y}{\beta_1 + 2\beta_2 \mathrm{Log}(y)}$$

where ϕ_i is the coefficient on climate variable i, β_1 is the coefficient on Log y (the logarithm of net household income) and β_2 the coefficient on Log y squared. Results are based on Model 3, which is the preferred model.

It is difficult to compare these estimates with ones from elsewhere. One reason is that other studies have used alternative, generally far simpler specifications of the climate. But because climate variables are often highly correlated, such a strategy risks wrongly attributing to one climate variable impacts more correctly attributed to another. A second obstacle is the fact that researchers have often measured particular variables in different ways, e.g., annual mean temperature versus heating and cooling degree days or January and July maximum daytime temperatures. In addition there are differences in geographical context and socioeconomic development (*MWTP* is related to income).

Despite these difficulties, it is possible to make a number of observations. To begin with, in spite of the fact that annual mean temperature and annual precipitation are included in many studies, in neither case is *MWTP* statistically significant even at the 10% level. It is of course important to avoid the trap of assuming that because a variable is not statistically significant it is unimportant. Temperature and precipitation might be important but *MWTP* estimates not sufficiently precise to exclude the possibility that *MWTP* is zero.

In contrast, *MWTP* for relative humidity and percentage of possible sunshine are statistically significant at the 1% level. The average household would be willing to pay €1,471 to increase the amount of sunshine by a single percentage point. A one percentage point increase in average relative humidity is worth −€1,928 to the average household.

Many studies into the value of the climate omit both relative humidity and sunshine. But it is interesting to note that in Blomquist *et al.* (1988) *MWTP* for sunshine is positive (USD 48.42 per percentage point) and *MWTP* for relative humidity is negative (USD 43.42 per percentage point).[7]

Our analysis includes a number of variables that are clearly related. For example, the average mean temperature and the number of frost days are clearly related, and so are annual precipitation and the number of rain days. We considered the possibility that these variables are statistically insignificant because of multicollinearity. However, an F-test reveals that these variables are jointly insignificant, even at the 10% level.[8] At the same time, however, the standard deviation in monthly mean temperatures is statistically significant at the 1% level as is the standard deviation in the monthly number of rain days. The implication is that households prefer a situation in which temperature is approximately constant throughout the year, rather than very cold in some months and very hot in other months.[9] The estimate of −€17,317.70 for a unit change in the standard deviation of temperature is however remarkably large, considering that our data include locations with a standard deviation of temperature ranging from 2.8 to 9.1. The value of −€9,353.04 per standard deviation for rain days is also surprisingly large, given that this variable ranges from 0.9 to 4.9.

The preference for climates not characterized by annual extremes of temperature is noted in other studies. In their hedonic analysis of the climate of Germany, Rehdanz and Maddison (2009) find that the implicit price of mean January temperatures is positive but the implicit price of July temperatures is negative. For Munich, the city

[7]There is interest in the possible use of bright light therapy for the treatment of nonseasonal depression (see, e.g., Tuunainen *et al.* (2004)).

[8]Srinivasan and Stewart (2004) conduct a hedonic analysis of households in England and Wales. They find that sunshine has a positive effect on house prices whereas temperature, precipitation and frost days are insignificant.

[9]Although latitude and the standard deviation in monthly mean temperatures are correlated latitude is still included as a separate control.

closest to the mean sample latitude of the respondents in our study, they place *MWTP* for mean January temperature at 1,568DM. The estimated *MWTP* for mean July temperatures for Munich is $-1{,}927$DM.[10]

The finding that households prefer climates where the number of rain days per month appears new to the literature. Englin (1996) presents a hedonic analysis with a positive implicit price for seasonal variation in precipitation. But his analysis relates only to Washington State and to precipitation instead of rain days.[11]

Although we investigate a different set of climate variables, methodologically our research has most in common with Brereton *et al.* (2008) and Ferreira and Moro (2010). Although large, the magnitude of our *MWTP* estimates appears conservative compared to the findings of Ferreira and Moro (2010), who estimate the *MWTP* for January mean daily temperatures for the average household in Ireland to be €15,585. And whilst Brereton *et al.* (2008) do not present *MWTP* estimates for climate variables, it is easy to construct them using the regression coefficient on minimum January temperatures and the coefficient on income. Combining this information with the sample mean value for net household income in our study gives a *MWTP* for minimum January temperatures of €48,643, which is over three times net household income.

Brereton *et al.* (2008) do not include relative humidity in their analysis and sunshine is statistically insignificant at the 10% level. Ferreira and Moro (2010) omit both variables.

We now consider a nonmonetary indicator of households' preferences for climate. Table 3 ranks countries by the quality of their climate (QOC). More specifically, countries are ranked from 1 to 19, with 1 being the country with the best climate. This index is calculated as follows

$$QOC_j = \sum_i \phi_i z_{ij}$$

where ϕ_i is the coefficient on climate variable i and z_{ij} is the level of climate variable i in location j.

The QOC index is obtained by averaging the QOC in the country's j constituent regions weighted according to their geographical area

$$QOC = \overline{QOC_j}$$

The ranking reveals that Mediterranean countries appear to have the best climate and Scandinavian ones the worst. In our dataset, the country with the best climate is Greece and the country with the worst Sweden.

Our QOC index, although similar to that proposed in Moro *et al.* (2008), differs in a fundamental way from indices which combine environmental indicators using weights

[10]Rehdanz and Maddison's 2005 global study also finds strong preferences for warmer temperatures in the coldest month and cooler temperatures in the hottest month.

[11]Most studies appear to employ precipitation rather than the number of rain days.

Table 3. Climate index by country.

Rank	Country
1	Greece
2	Spain
3	Portugal
4	Italy
5	France
6	Slovenia
7	Austria
8	Belgium
9	Great Britain
10	Germany
11	Belgium
12	Czech Republic
13	Slovakia
14	Netherlands
15	Denmark
16	Lithuania
17	Latvia
18	Estonia
19	Sweden

based on expert judgement. Blomquist *et al.* (1988) construct a QOL index for 253 US counties, using implicit prices from hedonic wage rate and hedonic house price regressions. Counties are ranked on the basis of climate, environmental quality and public goods. Their QOC index has the highest rank order correlation with overall QOL suggesting that climate is the most important determinant of QOL.

We have ranked 209 NUTS regions from 1 to 209, with 1 being the NUTS region with the best and 209 being the worst climate (supplementary material). The region with the best climate is the Canary Islands. The region with the worst climate is Northern Sweden. The poor performance of Northern Sweden is not attributable to latitude because this was included as a control variable.

Several Northern Italian and Austrian destinations also appear in the top 20. Without exception, these regions are popular skiing destinations, e.g., Valle d'Aosta in Italy. Climates that permit skiing boost life-satisfaction.

6. Conclusions

Previous researchers have used the hedonic technique to investigate the value of climate to households. Fewer researchers have attempted to explore the value of climate using data on life-satisfaction, even though a sizeable literature now looks at environmental factors as a determinant of life-satisfaction (as well as the impact of economic growth, inflation and unemployment).

In this paper, we use survey data on life-satisfaction to determine the value of climate to European households. We do so using NUTS level data over an area sufficiently large to ensure a significant variation in climate. Compared to other studies, we include a more comprehensive set of climate variables. We also investigate households' preferences for intra-annual variation in climate variables. At the same time, however, our focus is exclusively on life-satisfaction rather than on other measures of social well-being.

European households prefer more sunshine and lower relative humidity. Households also favor climates characterized by lower intra-annual variation in temperature and rain days. Annual mean temperature and annual precipitation have no statistically significant impact on life-satisfaction.

Our analysis allows us to rank regions in terms of QOC. Not only does the classic Mediterranean climate promote life-satisfaction, regions where winter sports are possible also lead to high levels of life-satisfaction. The climate of Scandinavia is associated with low life-satisfaction.

Future researchers of future research could use this approach to provide different QOL indices for different socioeconomic groups. There is no reason why different groups should rank environmental indicators in the same way. It would also be interesting to combine these results with scenario data on climate change in order to determine the regional impact of climate change. In the meantime, our results suggest that a simultaneous increase in humidity and the percentage of possible sunshine are ambiguous in terms of life satisfaction. And although households might prefer the bulk of any warming to occur in the winter time (thereby reducing the standard deviation of average temperatures), this might be offset by a change in the pattern of precipitation leading to drier summers (thereby increasing the standard deviation of rain days).

Supporting Information

Accompanying material on "Do Geographical Variations in Climate Influence Life-Satisfaction?" is available free of charge via the internet at http://www.worldscinet.com/cce/cce.html.

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