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Does Daily Sunshine make you Happy? Subjective Measures of Well-being and the Weather

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Abstract
This paper examines to what extent individual measures of well-being are correlated with daily weather patterns in the United Kingdom. Merging daily weather data with data from the British Household Panel Survey (BHPS) allows us to test whether measures of well-being are correlated with temperature, sunshine, rainfall and wind speed. We are able to make a strong case for causality due to 'randomness' of weather in addition to using regression methods that eliminate time-invariant individual level heterogeneity. Results suggest that some weather parameters (such as sunshine) are correlated with some measures of well-being (job satisfaction); however, in general the effect of weather on subjective measures of well-being is very small.

Keywords: weather, sunshine, happiness, satisfaction, well-being, BHPS

JEL classification: I10, J28

1. Introduction

In November 2010 the UK Office of National Statistics (ONS) set up the National Well-being Programme whose aim is to develop and publish an accepted list of national statistics that reports on the national well-being of the UK population. By supplementing, long-running, standard measures of economic well-being (GDP, income, employment and education) with more subjective measures (such as happiness, satisfaction, health) the idea is to provide a more holistic statistical representation of the state of society. This work has culminated in a first report entitled "Measuring National Well-being: Life in the UK, 2012" (ONS, 2012) which is the first official report that provides a statistical overview of the well-being of UK citizens. Results show that 76% of the UK population aged 16 or over has a high or medium satisfaction with their life overall and it seems reasonable to argue that the "economics of happiness" is becoming an increasingly important topic on the agenda of policy makers, citizens and social commentators.[2]

Another important factor which has experienced a significant increase in people's perception is the "economics of environment", in particular issues relating to climate change and global warming. Driven by the Intergovernmental Panel on Climate Change (IPCC) and a strong, and growing, literature on environmental change, policy makers

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[2] Using a different measure of life satisfaction an OECD comparison suggests that the UK achieves a score of 6.9 which is similar to Germany (7.0) and the United States (7.0). Countries such as Switzerland, Canada and Norway score highest with 7.5+ whilst Greece, Turkey and Hungary score lowest with less than 5.
http://www.oecdbetterlifeindex.org/topics/life-satisfaction/

and citizens are placing ever higher values on positive and negative externalities that are thought to be associated with climate and environmental issues. As an example, recent weather patterns in the UK suggest that a long-term shift in weather conditions may be occurring with the year 2012 proving to be the 2nd wettest year on record in the UK (Met Office, 2012) whilst for the U.S. it was the warmest year since records began (NOAA, 2012). Moreover, the Intergovernmental Panel on Climate Change (IPCC) predicts that average temperatures will rise by approximately 2°C over the next two decades (IPCC, 2007) whilst precipitation will increase by approximately 5-10% northern latitude countries.

In this paper, we follow a small literature that attempts to identify to what extent weather parameters influence individual behaviour and subjective well-being measures. We use local weather data from UK weather stations for the years 1991-2008 and merge this with annual household panel interviews in the British Household Panel Survey (BHPS). Our results show that initial correlations between weather parameters and indicators of well-being are statistically significant, however, once more sophisticated multivariate methods are used much of this correlation disappears. We thus argue that the causal effect of good (or bad) weather on subjective measures of well-being is negligible and that daily well-being is mainly driven by life events such as income, age, employment, marriage and other well researched factors.

The remainder of this paper is structured as follows. Section 2 reviews the literature and section 3 describes the data and key measures used in this analysis. Section 4 details the empirical strategy whilst section 5 presents the results. Finally, section 6 concludes.

2. Literature Review

The economics of happiness and subjective well-being has generated substantial interests amongst academics and policy makers; to the point that leading academics in the profession are calling for a philosophical shift away from a focus on economic prosperity and towards a focus on emotional prosperity (Stiglitz Commission 2009; Oswald, 2010; Stutzer and Frey, 2010). Within this maturing literature a large numbers of studies have attempted to determine factors that influence individual well-being and happiness (see Dolan, *et al*. 2008; Van Praag and Ferrer-i-Carbonell, 2008 or Blanchflower and Oswald, 2011 for an overview of this literature). Factors such as unemployment, poor health, age, income, social contact, gender, exercise, trust, income inequality, location and many more have all been shown to be highly correlated to various indicators of well-being. In addition, methodological improvements via random events, difference-in-differences designs and fixed effects estimation (Boyce and Oswald, 2012; Lorgelly and Lindley, 2008) have led to more robust claims of causality.

However, of the lesser examined determinants of well-being and happiness is the influence of weather patterns. This is somewhat surprising as we are all exposed, on daily basis, to various weather phenomena and there is a common belief that poor weather conditions decreases people's happiness, well-being and mood. To date, only some studies have examined the relationship between weather and individual well-being (see Barnston, 1988; Frijters and van Praag, 1998; Rehdaz and Maddison, 2005; Keller *et al.* 2005, Becchetti . *et al.* 2007, Denissen *et al.* 2008, Kööts *et al*. 2011, Tsutsui, 2012 and Murray, *et al*. 2013) and there does not appear to be a clear consensus on the results.

An early study by Barnson (1988), for example, followed 62 university students for a period of six week and results suggested that weather does indeed significantly influence the mood and behaviour of individuals, but only to a small extent. Males were more affected than females and good weather was found to be positively correlated to better a mood conditions. In addition, psychologically troubled students appeared to be more affected by weather conditions than other students. However, a disadvantage of this study is its relatively small sample size and its external validity.

In a larger cross-country comparison, Rehdaz and Maddison (2005) explore weather conditions and self-reported happiness in a panel of 67 countries. They find that after controlling for a range of factors (such as GDP, population density, life-expectancy, unemployment and more) climate variables have a significant effect on country-wide self-reported levels of happiness. They hypothesise that high-latitude countries (which are generally colder) might benefit from positive long-run temperature changes. However, the authors do warn that they could not investigate the effect of extreme weather events. In addition, a perennial problem of cross-country comparisons is that unobservable differences between country inhabitants may make comparability difficult, even after a various observable factors have been controlled for.

Frijters and Van Praag (1998) do not have this problem because they use individual country panel data from the Russian National Panel for 1993 till 1994. They find a positive relationship between well-being and temperature. For example, if temperature rose by 1°C, inhabitants in Moscow would need 13% less income to maintain the same level of well-being. In addition, rainfall also exerts a significant negative effect on reported levels of well-being and the authors argue that the effects of climate change – as reported by the IPCC – might lead the positive well-being effect for the majority of the Russian population. Other studies by Becchetti *et al.* (2007), Kööts *et al*. (2011) and Murray, *et al.* (2013) also find evidence that temperature, sunshine, humidity, fog, rain are related to indicators of happiness, life-satisfaction and affective experiences and thus there seems to be a growing body of literature that suggests that weather patterns influence the way we react and perceive well-being.

However, counter to this, Keller *et al.* (2005) analyse survey data from university respondents in the U.S. and find no evidence that better weather is associated with higher measures of well-being, although they do find evidence of interaction effects with the time of year. Individuals report feeling more positive during the spring, when the weather is warm, but less positive in the summer season during similar warm weather. Keller *et al*. argue that this is evidence of a seasonal affective disorder because individuals are deprived of warm weather and sunshine during the winter period and make up for this by increased happiness towards good weather during spring time. However, this effect is only temporary and disappears during the summer when good weather becomes the norm. Keller *et al.* (2005) is one of the first studies to suggest that weather factors have little to no influence on behaviour, however, external validity remains a problem due to the use of small, localised sample population used.

The most cited work is probably a study by Denissen *et al* (2008) who examine the effect of six weather parameters on positive/negative-affect and tiredness in an online diary study in Germany. They conclude that various weather phenomena did indeed have a statistically significant influence on mood indicators but that the average effect of this was small, although significant random variation appears to be present in individuals. Most strikingly, they find no evidence that sunshine is associated with more positive moods – a common perception in the public. In addition no differences by age or gender could be found. A strong advantage of their study is the fact they use large scale repetitive survey and are thus able to use fixed effect methods. This removes some uncertainty of self-selection in their analysis in addition to capturing all other individual level time-invariant unobservables. However, their study remains self-selective and extrapolation to a population level could be a potential issue.

Finally, Tsutsui (2012) correlates measures of happiness and depression against local weather conditions. His study is a diary study of 75 Osaka University students who were followed daily for 516 days. Result suggests that temperature is negatively related to happiness as is sunshine and humidity. However, some results appear to be driven by the fact that people are happier at night (because they are not working) when temperature and sunshine are low and there does not appear to be any correlation between wind speed, rainfall and other meteorological events.

It thus seems that much of the current evidence on weather and individual well-being is somewhat contradictory of each other. Some studies claim that there is little to no effect of weather variables on behavioural indicators whilst other studies suggest statistically small to large effects of various weather phenomena.

3. Data and descriptives

In this paper we make use of the British Household Panel Survey (BHPS) which contains detailed information on individual characteristics, life-outcomes and indicators of well-being in addition to the date-of-interview and regional location of a correspondent. The BHPS is a representative panel study that surveyed approximately 5,500 households containing 10,300 individuals aged 16 or above in the autumn of 1991. Our data is comprised of waves 1 to 18 (1991 to 2008) and we select all individuals who were surveyed.

The BHPS interviews are conducted annually and the majority of data is collected in the period between September to November within any given year (with some spill-over into December and the next calendar year). Our study is therefore mainly limited to the autumn season and results should be seen within this context.[3] However, a major advantage of the BHPS is that it contains 18 repeated waves of information over which weather and individual well-being variation can occur. This allows the application of within-based estimators which helps in the causal interpretation of our results.

The weather data used is historic data from 226 UK weather stations[4] obtained from the British Atmospheric Data Centre (BADC). Specifically we use the Met Office Integrated Data Archive System (MIDAS) whose station data contains geographical information in terms of latitude and longitude and information on the daily maximum, minimum and mean temperatures, wind speed, total daily rain fall and total daily sunshine. To merge weather stations into our data we make use of the conditional access version of the BHPS that contains geographical identifiers in the form 432 local authority districts and unitary authorities. We obtain the approximate centroid latitude and longitude for each local authority district/unitary authority and then use the haversine formula to find the minimum distance between any given weather station and each local authority[5]. The weather station and local authority with the smallest distance are then merged and this process is repeated for each of the 432 local authorities. On average the distance between each weather station and the centre of the local authority

[3] For example, as Keller *et al.* (2005) show, the relationship between mood and weather may change depending on the season of the year.

[4] See appendix table A1

[5] Where the distance *d*, between any two points is given by:

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2-\phi_1}{2}\right)+\cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right)$$

and r =radius of the earth in km, ϕ_1, ϕ_2 is the latitude of points 1 and 2 and λ_1, λ_2 is the longitude of points 1 and 2 is 18.1km. A descriptive summary and correlation matrix of the merged weather data is provided in Tables 1 and Figure 1:

Table 1: Summary of UK weather in BHPS on date of interview

	BHPS (1991 to 2008)			
	Mean	S.D.	Min.	Max.
TempMax (°C)	14.28	4.51	-4.00	31.30
TempMin (°C)	7.24	4.30	-13.10	18.50
TempMean (°C)	10.75	4.14	-6.25	24.10
WindSpeed (kn)	8.77	4.74	0.00	37.88
RainDaily (mm)	2.90	5.82	0.00	89.00
SunDaily (hrs)	3.36	3.18	0.00	15.00

Note: 96% of BHPS data is collected in September to November.

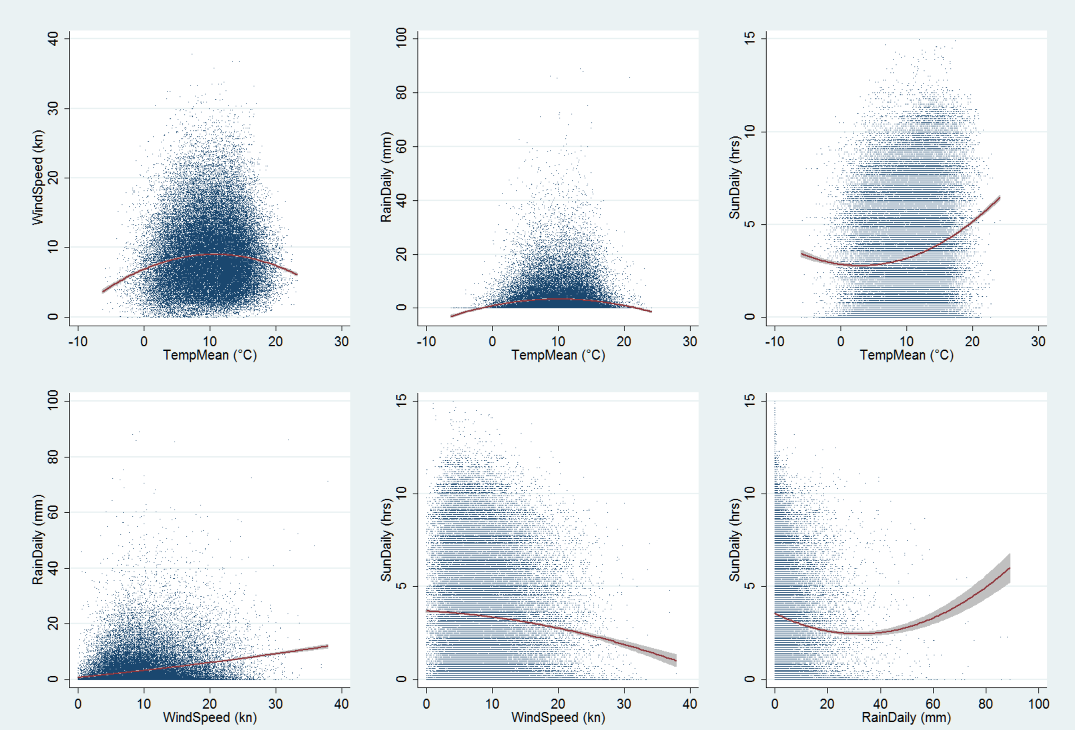
Table 1 shows that the maximum temperature experienced by some BHPS participants was 31°C whilst the minimum was -13°C. However, these are maximum and minimum temperatures within any given day of interview; on average BHPS participants experienced temperatures of 11°C during the day of the interview (commensurate with autumn weather), a wind speed of 9 knots (classified as a "gentle breeze" on the Beaufort scale), 3 mm of rain (low intensity rain) and 3 hours of sunshine. The "average autumn day" thus includes a gentle breeze, some low intensity rainfall, moderate temperatures and roughly half sunshine/half cloudy weather.

Figure 1 provides some insight into the relationship that our imputed weather variables have with each other.[6] Wind speed is generally low when temperatures are high or low but high when temperatures are more moderate (a quadratic fit suggests that wind speed is maximised at temperatures of 12°C). The same is true for rain fall; an inverted u-shape suggests that rainfall peaks when temperatures are a moderate 10°C. Sunshine has a quadratic relationship with temperature with more sunshine in low or high temperatures. Both rain and wind speed have a positive relationship with each other and a negative relationship with sunshine.[7] In general the data in Table 1 and Figure 1 behave "well" and we are thus satisfied that the weather data was successfully integrated into the BHPS.

[6] We avoid showing the correlation between average, minimum and maximum temperature as they are, by definition, highly correlated

[7] Very high amounts of rainfall and sunshine do appear to be positively correlated with each other but this is likely just an artefact particular weather events (such as small thunder storms).

Figure 1: Daily Weather Correlations (Autumn) in the BHPS on Date of Interview



BHPS 1991 - 2008. 96% of interviews are conducted in Sep-Nov. Quadratic fit with 95% confidence intervals

The BHPS includes a large amount of information on individual measures of health, well-being and attitudes towards life and economic circumstances. In this paper we decided to use six measures which are reflective of the well-being measures used in the first UK well-being report (ONS, 2012). We use subjective measures of health[8], well-being, happiness, job satisfaction, financial situation and friendship/family support and recode them so that higher values are associated with better well-being outcomes. An overview of the exact questions used is provided in Table 3. The majority of these questions are based on traditional Likert scales whilst the subjective wealth question is based on an ordinal structure. A derived subjective well-being variable, which is measured on a continuous scale, is also available and is simply the summation of scores from all twelve general health questions (GHQ). The same applies to the support variable which is derived from five family/friendship support questions. The presence of so many Likert scale variables and their implication for estimation will be discussed further in the methodology section.

Table 3: Dependent variables used from BHPS

[8] It should be noted that this question specifically asks respondents to reflect back on their health status over the last 12 months. As such, any results of weather significantly affecting health should be interpreted as weather biasing individual's responses rather than directly affecting their health or well-being. This applies to financial well-being and friendship questions similarly.

Variable		Question	Measure	Average
BHPS	Renamed			
ghql	happy	Have you recently been feeling reasonably happy, all all things considered ?	Likert Scale (1 to 4)	2.98
jbsat	jbsat	All things considered, how satisfied or dissatisfied are you with your present job?	Likert Scale (1 to 7)	5.40
fisit	finance	How well would you say you yourself are managing financially these days?	Ordinal (1 to 5)	3.85
hlghq1	wellbeing	Subjective wellbeing from twelve general health questions (GHQ)	Continuous (1 to 36)	24.86
ssup	support	Is there someone who will listen/help in crisis/relax/appreciate you/count on	Continuous (1 to 10)	7.33
hlstat	health	Please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say that your health has on the whole been?	Likert Scale (1 to 5)	3.82

Variables were renamed in this study to aid identification

Table 4 provides a first summary overview of the correlation between the imputed weather variables and our measures of subjective individual well-being. In addition to correlating measures of well-being to weather patterns on the date of interview we also compute a 3-day average prior to the date of interview. This allows us to examine whether longer periods of adverse/favourable weather prior to the interview have a more significant impact on well-being when compared to short-term weather variations.

Results suggest that, in general, there is little correlation between measures of well-being and the weather. None of the correlation coefficients exceed an absolute value of 0.05 which suggests that, at least in a descriptive setting, there is little interaction between weather and well-being responses. However, the raw size of our data does produce some statistically significant relationships. In particular, there is a statistically significant negative correlation between temperature/sun and job satisfaction indicating that those who are working are less satisfied with their jobs on warm and sunny days. There also appears to be a positive relationship between temperature/sun and self-reported financial well-being, with better weather resulting in more positive financial well-being responses. Finally, self-reported support has a positive relationship with good weather (higher temperature, more sun, less rain and less wind) whilst self-reported health over the last 12 months also exhibits a positive relationship with good weather. Self-reported happiness and general well-being do not appear to be significantly correlated with weather patterns.

The 3-average correlations mimic those of the daily weather which suggest that long periods of consistent ‘good’ or ‘bad’ weather have similar effects on these indicators of well-being. However, the correlations in Table 4 are only descriptive and do not control for self-selection into particular areas/climates and neither do they control for time/seasonal effects. It is therefore important to examine the effect of weather on self-reported measures of well-being in a multivariate framework which is outlined in the next section.

Table 4: Pairwise correlation coefficients of weather and measures of subjective well-being

	BHPS					
	happy	jbsat	finance	wellbeing	support	health
Daily						
TempMean	0.001	-0.007*	0.017*	-0.002	0.026*	0.033*
RainDaily	-0.002	0.006*	-0.001	0.001	-0.051*	-0.002
SunDaily	0.002	-0.012*	0.009*	-0.003	0.015*	0.010*
WindSpeed	-0.004*	0.000	-0.005*	0.003	-0.074*	-0.001
3 Day Average						
TempMean3Day	0.000	-0.007*	0.018*	-0.003	0.015*	0.035*
RainDaily3Day	-0.004	0.004	-0.002	0.005	-0.082*	0.003
SunDaily3Day	0.004	-0.009*	0.015*	-0.006*	0.032*	0.016*
WindSpeed3Day	-0.007*	-0.002	-0.006*	0.006*	-0.091*	-0.001

4. Methodology

To investigate the effect that weather conditions have on individual subjective measures of well-being we specify a general model that regresses observed local weather patterns on the date of interview against the aforementioned indicators of well-being:

$$y_{it} = \mathbf{Weather}'_{it}\beta_k + \mathbf{x}'_{it}\lambda_x + \varepsilon_{it} \quad (1)$$

where y_{it} is the dependent variable (happiness, job satisfaction, financial satisfaction, well-being, support networks and health status) for individual *i* in time *t*, $\mathbf{Weather}_{it}$ is a vector of variables which measure the local weather conditions at the time of interview (average temperature, average rain, sun light and average wind speed per day), $\mathbf{x}_{it}$ is a vector individuals and other explanatory characteristics and ε_{it} is a normally distributed error term.

In dealing with the parameter estimates of interest, β_k, we need to consider all four terms in (1) to ensure that we estimate a causal, non-spurious, effect of weather, in addition to achieving a correct functional form. The debate surrounding causality is non-trivial, since although it might be suggested that weather is a truly 'random' event, this is not necessarily the case when it comes to panel survey data. For example, we may need to consider the day of interview since interviews are conducted on a permanent basis and prior research has shown that individuals report being more happy during non-working days. In addition, seasonal patterns, such as winter time, may dampen the mood of all individuals in the panel and should be controlled for (seasonal affective disorder).[9] Regional effects must also be considered since parts of the United Kingdom are historically more wet and windy than others (e.g. Scotland). Finally, wealthy or elderly individuals may decide to locate to more temperate areas in the UK and this should likewise be controlled for.

Therefore, to ensure that local weather conditions are exogenous we include a series of individual level controls in the vector $\mathbf{x}_{it}$ that includes; gender, age group, ethnicity, disability, employment status, educational qualifications, marital status, number of

[9] This is less of a problem in our data as most of the interviews are conducted in the autumn time period. Nonetheless, some data is collected during the winter months of December, January and February.

children and family income quintiles. We also include hour, day and month of interview dummies in addition to regional controls.

Nonetheless, these controls do not fully rule out other unobserved factors that may jointly influence local weather conditions and measures of well-being. For example, it might be that some people have certain 'life-attitudes' which causes them to live in a particular UK regions, such as the south-east which generally has milder climate, and in addition causes them to report higher levels of well-being. Alternatively, additional unobserved measures of wealth or affluence might cause such a phenomenon where locale (and thus weather conditions) and well-being are jointly correlated with such an unobservable factor.

To deal with these potential unobservable confounders we decompose the error term ε_{it} in equation (1) so that:

$$y_{it} = \mathbf{Weather}'_{it}\beta_k + \mathbf{x}'_{it}\lambda_x + v_i + \tau_t + u_{it} \tag{2}$$

ε_{it} now comprises a general time effect, τ_t, an individual specific time-invariant error, v_i, and a time-varying individual specific error, u_{it}. τ_t can be thought of as representing macro-level shocks which affect the population as a whole and can be handled via the inclusion of dummy variables representing the wave at which an observation was made. v_i are person specific effects which vary only across individuals (such a long-run person specific attitudes) and not across time whilst u_{it} are the remaining shocks which vary across time and individuals. At the cost of higher standard error's a convenient solution to the unobservable problem is to eliminate v_i by differencing all variables from their person-specific mean:

$$\tilde{y}_{it} = \widetilde{\mathbf{Weather}}'_{it}\beta_k + \tilde{\mathbf{x}}'_{it}\lambda_x + \tilde{v}_i + \tilde{\tau}_t + \tilde{u}_{it} \tag{3}$$

where $\tilde{y}_{it} = y_{it} - \bar{y}_i$, $\tilde{\mathbf{x}}_{it} = \mathbf{x}_{it} - \bar{\mathbf{x}}_i$, etc. This is the fixed effects estimator which has the attractive property that $\tilde{v}_i = v_i - \bar{v}_i = 0$, implying that all unobserved (and observed) time-invariant individual confounders are 'differenced out' of the equation.[10]

However, the fixed estimator is generally used in a linear panel data setting, i.e. when the dependent variable is in a continuous form and many of the dependent variables used in this study take ordinal forms (such as Likert scales) which preferably require non-linear modelling techniques, such as ordered- or multinomial logit models. Unfortunately, such models are notoriously difficult to reconcile with traditional (linear) fixed-effect estimation in addition to be being more complex to interpret. In the interest of homogeneity and interpretability we therefore decide to estimate all models in a linear setting, even though this may not be the most appropriate method (for example, linear modelling makes an explicit assumption that the "distance" between very poor health and poor health is the same as poor health and fair health). However,

[10] We could obtain a more efficient estimator by allowing individual specific intercepts and assuming that these intercepts are normally distributed around a mean of zero. Estimating the variance of v_i will then yield the random effects estimator. However, if either of the individual-specific errors are correlated with $\mathbf{Weather}'_{it}$ then the estimates of β_k will be biased and inconsistent. We test for this using the Hausman test and in all specification a fixed effect estimator is preferred.

we argue that method misspecification is preferably over the possibility of contaminating estimates with unobservable confounders. For example, Ferrer-i-Carbonell and Frijters (2004) find that treating happiness data as cardinal rather than ordinal does not have a substantial impact on their estimated results whilst using fixed effects does significantly change results.

Finally, to ensure that we take into account functional form in the relationship between weather and well-being, we also split the variables in the vector $\mathbf{Weather}'_{it}$ into categorical groups. This allows for a more flexible non-linear relationship between various weather intensities (such as very high or very low temperatures) and avoids misspecification through linear or polynomial terms. Moreover, in addition to regressing weather on the day of interview against measures of well-being we also use a 3 and 5 day averages to test whether long-run weather behaviour significantly impacts on well-being.

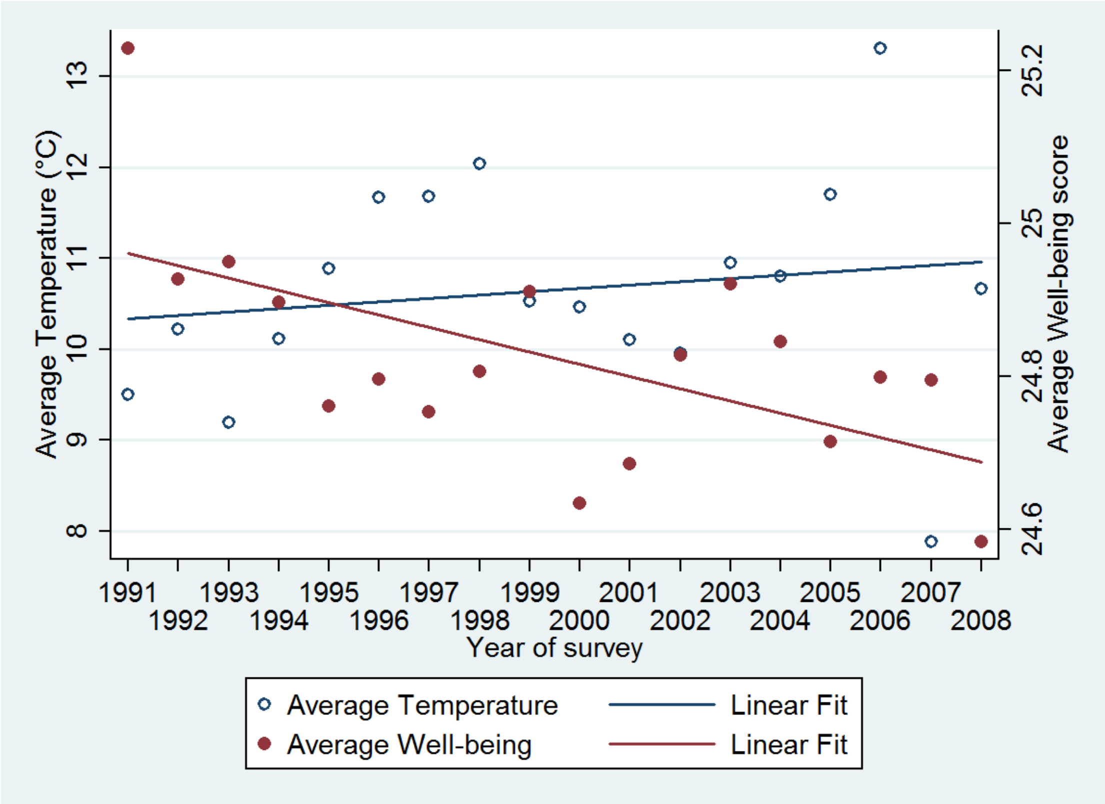
5. Results

In this section we present the results from various alternative regression specifications to ensure that our results are robust and consistent. Table 5 investigates the impact of using various weather variables on our six indicators of well-being. Table 6 examine whether there are potential non-linear effects of weather on measures of subjective well-being (i.e. warm weather is related positively to happiness but extremely warm weather is negatively related to happiness) whilst also examining 3-day averages. Finally, Table 7 introduces a custom dummy variable to represent “good” and “poor” weather conditions which amalgamates the four different weather parameters.

Before turning to Table 5 it is briefly worth mentioning the impact that the various control variables have on our resulting estimates. Table A1 in the appendix provides a detailed overview of how the weather coefficients evolve as additional regressors are loaded into the equations and the overall conclusion is that virtually none of the controls have a significant impact on the weather coefficients. To a large extent this is reassuring as a primary argument behind this weather data is that is uniquely random and should not be influenced by confounding variables.

However, in analysing the variable loadings closer we see that the inclusion of wave dummies can, in some regressions, have a significant impact on the estimated weather coefficients. For example, there appears to be a statistically significant negative relationship between weather and well-being which becomes positive and non-significant once waves dummies are controlled for (regressions (5) to (6) in Table A1). This phenomenon is prevalent for regressions that include well-being scores, financial well-being, job satisfaction, family & friendship support and self-assessed health and in most cases the sign of the relationship switches. The explanation for this lies in the fact that weather and many of the dependent variables are not stable over time but exhibit either a rising or falling trends. Figure 2 exemplifies this and shows that over time there is an increasing temperature trend and a decreasing well-being trend. It is therefore important to note that when using panel data and weather variables, underlying time trends should be controlled for as otherwise spurious correlations may appear to exist between daily weather patterns and outcome measures.

Figure 2: Time trending between temperature and well-being score



Source: BHPS 1991-2008

Turning now to our estimates in Table 5, results suggest that the causal effect of weather on individual measures of well-being is generally statistically insignificant. The main statistically significant effect comes from daily sunshine which suggests that a 1 hour increase in daily sunshine reduces job satisfaction by -0.005. In comparison, being interviewed on a working day of the week (except for Friday)[11] reduces job satisfaction by -0.05 to -0.08. The average job satisfaction score of an individual is 5.4 with range 1 to 7 which further suggests that the estimated effect of sunshine on job satisfaction is extremely small. For example, a 10 hour increase in sunshine would cause job satisfaction to decrease by approximately 0.05 points which equates to about 1% less job satisfaction.[12] In addition to finding an effect of temperature on job satisfaction there is also a small, but statistically significant, effect of wind speed on measures of happiness and financial well-being, however, both effects are even smaller.

Table 5: The effect of weather variables on subjective measures of well-being.

[11] These results not shown in the Table 5 but are in the controls. Full output available upon request.

[12] A more detailed analysis by occupation type suggests that this effect on job satisfaction is strongest for individuals who work in services and non-manual occupations. Individuals in occupations such as farmers, agricultural workers and unskilled manual labourers only have a daily sun coefficient of -0.002 (0.003), which is about half that reported in table 5. This suggests that office type jobs are most affected by sunny autumn weather days.

	happy	wellbeing	finance	jbsat	support	health
TempMean	0.001	0.004	0.001	-0.003	0.001	0.000
	(0.001)	(0.005)	(0.001)	(0.002)	(0.003)	(0.001)
SunDaily	0.001	0.005	0.000	-0.005**	0.001	-0.001
	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)
RainDaily	-0.000	-0.002	0.000	0.001	-0.001	0.000
	(0.000)	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)
WindSpeed	-0.001*	-0.003	-0.001*	-0.001	0.001	-0.000
	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)	(0.000)
Hour of day	yes	yes	yes	yes	yes	yes
Day of week	yes	yes	yes	yes	yes	yes
Month of year	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes
Wave dummies	yes	yes	yes	yes	yes	yes
Individual level controls	yes	yes	yes	yes	yes	yes
Constant	3.088***	25.602***	3.471***	5.724***	8.090***	4.023***
	(0.043)	(0.393)	(0.064)	(0.175)	(0.212)	(0.064)
N	166423	164917	170070	89855	78984	163865

Fixed effects with cluster standard errors. Individual level controls include gender, age, ethnicity, marriage, child, job status, household income and education indicators. s.e's clustered on weather stations

It thus appears that daily weather patterns have relatively little effect on measures of individual subjective well-being. However, the non-results in Table 5 could the result of a too restrictive functional form being imposed on the data. We therefore split the continuous weather indicator (temperature, rain fall, sunshine and wind speed) into categorical dummies and test whether individual dummies are statistically significant and whether non-linear relationships between the weather and our measures of well-being exist. We also test whether measures of well-being are more responsive to longer periods of particular weather by testing 3-day weather averages[13] because it may be possible that people are non-responsive to daily weather changes but more responsive to longer periods of rain and sunshine. Results are presented in Table 6 which reports the coefficient on the various weather dummies in addition to the 1-day and 3-day weather averages.

[13] 5-day weather average were also tested and showed similar results to 3-day weather averages.

Table 6: The effect of weather variables on subjective measures of well-being – testing for non-linear effects

	Daily						3 Day Averages					
	happy	wellbeing	finance	jbsat	support	health	happy	wellbeing	finance	jbsat	support	health
Average Daily Temperature (Ref: -15°C to 0°C)												
0°C to 5°C	-0.024	-0.318*	0.050	-0.053	0.111	0.019	-0.006	-0.044	0.029	0.069	0.002	-0.001
	(0.022)	(0.159)	(0.036)	(0.065)	(0.120)	(0.027)	(0.023)	(0.199)	(0.040)	(0.080)	(0.147)	(0.031)
5°C to 10°C	-0.021	-0.247	0.060	-0.074	0.059	0.022	-0.009	-0.060	0.011	0.052	0.032	-0.003
	(0.021)	(0.165)	(0.036)	(0.064)	(0.122)	(0.027)	(0.024)	(0.206)	(0.039)	(0.078)	(0.144)	(0.030)
10°C to 15°C	-0.015	-0.212	0.061	-0.067	0.071	0.026	0.006	0.032	0.021	0.059	0.018	0.004
	(0.021)	(0.166)	(0.036)	(0.066)	(0.122)	(0.027)	(0.025)	(0.212)	(0.039)	(0.079)	(0.147)	(0.031)
15°C to 20°C	-0.010	-0.209	0.056	-0.106	0.054	0.023	0.012	0.008	0.017	0.044	-0.036	0.003
	(0.021)	(0.170)	(0.037)	(0.068)	(0.126)	(0.028)	(0.025)	(0.212)	(0.040)	(0.082)	(0.147)	(0.033)
20°C or more	0.027	-0.121	0.053	-0.037	0.069	0.014	0.018	-0.274	0.019	-0.001	-0.412	-0.053
	(0.031)	(0.243)	(0.048)	(0.098)	(0.171)	(0.041)	(0.049)	(0.376)	(0.083)	(0.156)	(0.264)	(0.072)
Daily sunshine (Ref: 0 hours per day)												
0.1 to 2 hours	0.005	0.087*	-0.002	-0.008	0.010	-0.003	-0.009	0.163	-0.011	0.041	-0.058	-0.009
	(0.005)	(0.040)	(0.007)	(0.014)	(0.027)	(0.006)	(0.015)	(0.112)	(0.022)	(0.044)	(0.058)	(0.017)
2 to 4 hours	0.001	0.044	-0.004	-0.029*	-0.034	-0.003	-0.005	0.108	-0.004	0.059	-0.047	-0.010
	(0.006)	(0.048)	(0.007)	(0.014)	(0.029)	(0.007)	(0.015)	(0.115)	(0.023)	(0.044)	(0.061)	(0.017)
4 to 6 hours	0.008	0.095*	-0.006	-0.026	-0.000	-0.004	-0.005	0.122	0.000	0.025	-0.053	-0.014
	(0.005)	(0.044)	(0.008)	(0.014)	(0.031)	(0.007)	(0.015)	(0.114)	(0.023)	(0.045)	(0.062)	(0.018)
6 to 8 hours	0.005	0.059	-0.004	-0.027	-0.008	-0.001	0.010	0.007	0.005	0.054	-0.059	-0.016
	(0.006)	(0.045)	(0.008)	(0.016)	(0.031)	(0.007)	(0.017)	(0.127)	(0.023)	(0.045)	(0.065)	(0.018)
8 hours or more	0.007	0.084	0.008	-0.045**	0.019	-0.008	0.008	0.069	-0.010	0.019	-0.008	-0.010
	(0.007)	(0.046)	(0.009)	(0.017)	(0.037)	(0.008)	(0.017)	(0.123)	(0.026)	(0.052)	(0.074)	(0.022)
Daily Rainfall (Ref: 0mm per day)												
0.1 to 1mm	-0.002	-0.003	-0.003	-0.015	-0.002	-0.005	0.008	0.021	0.001	0.011	-0.050	-0.006
	(0.005)	(0.037)	(0.007)	(0.014)	(0.025)	(0.005)	(0.005)	(0.042)	(0.008)	(0.017)	(0.026)	(0.007)
1 to 2mm	0.004	0.026	-0.005	0.017	-0.030	0.010	0.004	0.011	0.003	0.011	-0.031	-0.005
	(0.006)	(0.049)	(0.009)	(0.018)	(0.032)	(0.008)	(0.006)	(0.050)	(0.009)	(0.019)	(0.032)	(0.009)
2 to 4mm	-0.009	-0.003	-0.000	0.021	0.039	-0.007	0.007	0.016	0.004	0.012	-0.067*	-0.005
	(0.006)	(0.046)	(0.009)	(0.015)	(0.028)	(0.006)	(0.006)	(0.047)	(0.009)	(0.018)	(0.031)	(0.008)
4 to 6mm	-0.009	-0.058	0.010	0.013	-0.025	0.012	0.007	-0.003	-0.003	0.015	-0.077*	-0.005
	(0.007)	(0.059)	(0.010)	(0.018)	(0.035)	(0.009)	(0.008)	(0.058)	(0.010)	(0.021)	(0.037)	(0.009)
6 to 8mm	0.006	0.003	0.016	0.016	0.019	-0.000	-0.002	-0.062	0.012	0.003	-0.055	-0.024*
	(0.008)	(0.065)	(0.011)	(0.024)	(0.044)	(0.010)	(0.009)	(0.065)	(0.011)	(0.023)	(0.043)	(0.010)
8mm or more	-0.004	-0.069	-0.003	0.006	-0.022	-0.002	0.009	0.065	0.005	0.018	-0.030	-0.004
	(0.005)	(0.040)	(0.008)	(0.016)	(0.031)	(0.007)	(0.008)	(0.060)	(0.010)	(0.024)	(0.038)	(0.010)
Average Daily Windspeed (Ref: 0 to 2kn)												
2 to 4kn	-0.025*	-0.205*	-0.016	-0.039	0.014	0.002	-0.011	-0.104	0.002	0.118*	-0.121	-0.008
	(0.010)	(0.084)	(0.014)	(0.029)	(0.047)	(0.013)	(0.020)	(0.172)	(0.023)	(0.056)	(0.111)	(0.021)
4 to 6kn	-0.027**	-0.194*	-0.006	-0.029	-0.036	-0.004	-0.015	-0.129	-0.010	0.096	-0.132	-0.007
	(0.010)	(0.082)	(0.013)	(0.029)	(0.048)	(0.013)	(0.019)	(0.168)	(0.023)	(0.054)	(0.107)	(0.022)
6 to 8kn	-0.022*	-0.180*	-0.008	-0.036	-0.013	0.002	-0.019	-0.153	-0.005	0.102	-0.125	-0.007
	(0.010)	(0.076)	(0.013)	(0.029)	(0.049)	(0.012)	(0.019)	(0.167)	(0.022)	(0.053)	(0.106)	(0.022)
8 to 10kn	-0.023*	-0.179*	-0.015	-0.041	-0.003	-0.000	-0.020	-0.156	-0.012	0.083	-0.134	-0.014
	(0.010)	(0.077)	(0.014)	(0.030)	(0.050)	(0.013)	(0.019)	(0.168)	(0.023)	(0.054)	(0.107)	(0.022)
10 to 15kn	-0.025*	-0.188*	-0.013	-0.038	0.015	-0.002	-0.025	-0.182	-0.012	0.091	-0.115	-0.004
	(0.010)	(0.076)	(0.014)	(0.031)	(0.047)	(0.012)	(0.019)	(0.167)	(0.023)	(0.054)	(0.109)	(0.022)
15kn or more	-0.034**	-0.239**	-0.028	-0.036	0.002	-0.006	-0.033	-0.209	-0.018	0.075	-0.124	-0.012
	(0.011)	(0.085)	(0.015)	(0.033)	(0.051)	(0.013)	(0.019)	(0.172)	(0.025)	(0.058)	(0.109)	(0.023)
Hour of day	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day of week	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Month of year	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Individual level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	3.137***	25.986***	3.429***	5.797***	8.049***	4.007***	3.109***	25.860***	3.470***	5.467***	8.325***	4.049***
	(0.051)	(0.431)	(0.069)	(0.185)	(0.255)	(0.070)	(0.059)	(0.521)	(0.077)	(0.206)	(0.294)	(0.075)
N	166278	164773	169920	89779	78948	163724	166278	164773	169920	89779	78948	163724

Fixed effects with cluster standard errors. Individual level controls include gender, age, ethnicity, marriage, child, job status, household income and education indicators. s.e's clustered on weather stations

Results in Table 6 suggest that the insignificance of weather on individual measures of subjective well-being is maintained. Daily temperature is not statically significant in any of the regressions whilst daily rainfall is also mostly statistically insignificant. The exception is that longer periods of moderate rain fall results in lower self-reported levels of family & friendship support. Hours of daily sunshine appears to be statistically insignificant for most measures of well-being except for job-satisfaction where longer periods of sunshine result in lower job-satisfaction. However, there is no suggestion that this effect might be non-linear and it also not maintained into the medium run 3-day weather results. This suggests that individuals quickly adjust too sunlight conditions and there is no adverse effect of long term sunshine on job satisfaction. Finally, results for windfall suggest that windy day's decrease responses to general well-being and happiness questions but do not statistically affect the other measures of well-being.

However, it seems strange that of the four weather characteristics only wind would have a statistically significant effect on happiness and well-being. We argue that this result is likely an artefact of weather being a complex combination of temperature, sunshine, rainfall and wind speed. So far we treated each component independently and therefore as a final test we create three new weather categories defined as normal, poor and good weather conditions, where:

$$weather = \begin{cases} 1 \text{ (normal weather)} = \text{ all other weather conditions} \\ 2 \text{ (bad weather)} = \text{temp} < 10, \text{ wind} > 7, \text{ rain} > 0 \text{ and sun} = 0 \\ 3 \text{ (good weather)} = \text{temp} > 15, \text{ wind} < 7, \text{ rain} = 0 \text{ and sun} > 3 \end{cases}$$

These weather conditions are arbitrarily defined but are the author's attempt to classify certain days into "good" or "poor" weather. This classification is such that approximately 87% of all weather days are classified as normal, 8% are classified as poor with low temperatures, moderate wind, rain and no sunshine, and 5% are classified as good weather with high temperatures, low wind, no rain and more than 3 hours of sunshine.

Table 7 reports the results of "good" (bad) weather conditions with reference to "normal" weather days as previously outlined. We test 1-day and 3-day weather conditions[14] against indicators of subjective well-being and results suggest that many of our previous findings are substantiated; mainly that good (or bad) weather conditions have very little influence on individual well-being. However, there is now some evidence that longer periods of good weather increases self-reported well-being and health outcomes. This is interesting as it suggests that the previous composition of weather variables – where all four weather phenomena were loaded independently into the regressions – could not reveal the complex and multi-dimensional nature of weather. Once the four independent weather categories of temperature, wind, sun and rain are combined into a generic indicator of 'good' or 'bad' weather there is now some evidence that good weather is associated with better feelings of well-being. However, it is still difficult to conclude that there is a systematic relationship between weather and subjective measures of well-being with so few statistically significant effects in Table 7.

[14] 5-day averages were also tested and showed similar results to 3-day averages. Results available upon request.

Table 7: The effect of weather variables on subjective measures of well-being – good weather vs. bad weather

	happy	wellbeing	finance	jbsat	support	health
Daily Weather Days (reference: normal)						
Bad Weather	-0.009	-0.037	0.001	0.002	0.009	-0.003
	(0.005)	(0.046)	(0.007)	(0.015)	(0.024)	(0.007)
Good Weather	0.006	0.057	0.007	-0.028	0.021	0.002
	(0.006)	(0.048)	(0.009)	(0.018)	(0.029)	(0.008)
Additional controls	yes	yes	yes	yes	yes	yes
Constant	3.110***	25.826***	3.504***	5.655***	8.375***	3.999***
	(0.037)	(0.319)	(0.060)	(0.148)	(0.160)	(0.058)
N	166278	164773	169920	89779	78948	163724
3-Day Weather Days (reference: normal)						
Bad Weather	-0.007	-0.067	-0.006	0.012	0.015	-0.010
	(0.005)	(0.040)	(0.007)	(0.014)	(0.024)	(0.006)
Good Weather	0.010	0.150**	-0.004	-0.006	0.043	0.018*
	(0.007)	(0.054)	(0.010)	(0.023)	(0.038)	(0.008)
Additional controls	yes	yes	yes	yes	yes	yes
Constant	3.111***	25.825***	3.505***	5.652***	8.373***	3.999***
	(0.037)	(0.319)	(0.060)	(0.148)	(0.160)	(0.058)
N	166278	164773	169920	89779	78948	163724

Additional controls include: gender, age groups, ethnicity, marriage, children, education, job status and family income indicators. s.e.'s clustered on weather stations

6. Discussion and Conclusions

We thus conclude, after having analysed the effect of various weather parameters in alternate specifications, that the causal impact of daily, and short run, weather conditions on measures of individual well-being is statistically insignificant. Weather conditions therefore do not play a causal role in influencing how individuals respond to behavioural questions and our findings are contrary to some of the previous literary findings which suggest that a significant relationship between weather and well-being exists.[15]

In seeking to explain such null-findings we argue that data and methods matter. As can be seen in Table 4, univariate correlations appear to suggest a broad significant correlation between weather and measures of well-being. When moving towards a multivariate framework much of this significance disappears, although even here,

[15] See for example Frijters and Van Praag, (1998), Rehdaz and Maddison, (2005) or Murray *et al.* (2013)

variable choice matters (as highlighted in Table A1). Compared to some of the previous literature, our study uses an improved data source (panel vs. cross-sectional surveys/diary studies) and improved methods (fixed effects with detailed socio-economic controls) and we argue that our null-finding is an important contribution literature.

However, our results have also found a small, but statistically significant, relationship between weather and job satisfaction where better weather conditions decrease job satisfaction, especially for indoor type jobs. It should be noted, though, that this effect remains marginal and is unlikely to result in constructive policy or industrial advice (i.e. employers should implement job satisfaction policies on good weather days). Nonetheless, this finding may be useful for other studies investigating the causal effect of job satisfaction on some other outcome variable as we have opened up the possibility of using weather as an instrumental variable for job satisfaction. Finally, our results also show some evidence that longer periods of 'good' weather is indeed related to better feelings of well-being and happiness. However, this effect remains small.

To conclude, we have shown that the UK population is relatively resilient to daily and short-run weather variations during the period 1991 to 2008 and no significant relationship between weather and indicators of subjective well-being can be found. Our results are in line with previous research by Watson (2000) and Keller *et al.* (2005) who also called into question the commonly held belief that weather effects mood and well-being and our research substantially strengthens this strand of belief.

Extrapolating our results suggests that the increase in extreme type weather events, such as higher global temperatures or more rain are unlikely to directly significantly affect the well-being of the UK population. However, it is possible that extreme weather events may indirectly affect measures of well-being via droughts, floods or other personal life events and we propose that this as a potential avenue of future research. Finally, it should be noted that much of the BHPS data is collected in the autumn and that further work with data spanning the entire calendar year is warranted.

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Appendix

Fig A1. MIDAS weather stations merged into the BHPS

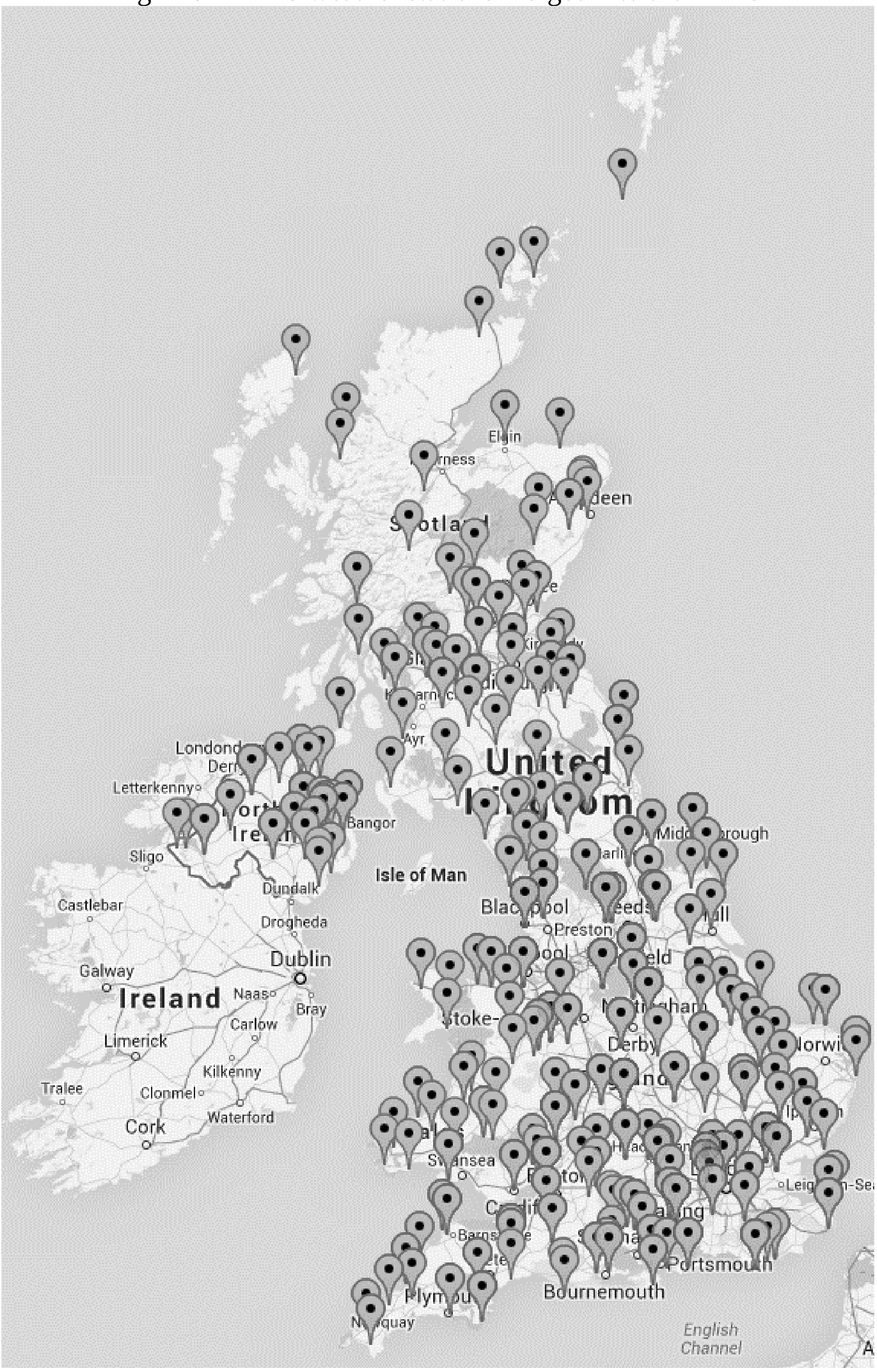

Table A1. Stepwise inclusion of control variables

	(1) happy	(2) happy	(3) happy	(4) happy	(5) happy	(6) happy	(7) happy
TempMean	0.000	0.000	0.000	-0.000	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
SunDaily	0.001	0.001	0.001	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RainDaily	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WindSpeed	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	2.987***	2.993***	2.998***	3.006***	3.043***	3.062***	3.088***
	(0.006)	(0.012)	(0.014)	(0.016)	(0.030)	(0.030)	(0.043)
N	167366	167237	167237	167237	166423	166423	166423

	(1) wellbeing	(2) wellbeing	(3) wellbeing	(4) wellbeing	(5) wellbeing	(6) wellbeing	(7) wellbeing
TempMean	0.004	0.004	0.004	-0.011*	-0.011*	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
SunDaily	0.005	0.005	0.005	0.001	0.001	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
RainDaily	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
WindSpeed	-0.005	-0.005	-0.005	-0.003	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	24.816***	24.857***	24.944***	25.198***	25.230***	25.673***	25.602***
	(0.048)	(0.092)	(0.106)	(0.120)	(0.247)	(0.244)	(0.393)
N	165854	165728	165728	165728	164917	164917	164917

	(1) fisit	(2) fisit	(3) fisit	(4) fisit	(5) fisit	(6) fisit	(7) fisit
TempMean	0.008***	0.009***	0.009***	0.008***	0.008***	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SunDaily	0.003***	0.003***	0.003***	0.004***	0.003***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RainDaily	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WindSpeed	-0.001*	-0.001*	-0.001*	-0.001	-0.001	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	3.756***	3.766***	3.787***	3.799***	3.768***	3.703***	3.471***
	(0.010)	(0.018)	(0.021)	(0.023)	(0.050)	(0.052)	(0.064)
N	172332	171737	171737	171737	170912	170912	170070

	(1) jbsat	(2) jbsat	(3) jbsat	(4) jbsat	(5) jbsat	(6) jbsat	(7) jbsat
TempMean	-0.003*	-0.003*	-0.003*	-0.006**	-0.006**	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SunDaily	-0.005***	-0.005***	-0.005***	-0.006***	-0.006***	-0.004**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RainDaily	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WindSpeed	-0.001	-0.001	-0.001	0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	5.451***	5.499***	5.555***	5.599***	5.630***	5.659***	5.724***
	(0.016)	(0.034)	(0.036)	(0.040)	(0.119)	(0.119)	(0.175)
N	91196	90874	90874	90874	90327	90327	89855

	(1) support	(2) support	(3) support	(4) support	(5) support	(6) support	(7) support
TempMean	0.008	0.008	0.008	-0.026***	-0.026***	0.001	0.001
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.003)	(0.003)
SunDaily	-0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)
RainDaily	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
WindSpeed	-0.034***	-0.034***	-0.034***	-0.023***	-0.022***	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	7.409***	7.174***	7.253***	7.697***	7.966***	8.142***	8.090***
	(0.107)	(0.143)	(0.152)	(0.159)	(0.228)	(0.119)	(0.212)
N	79382	79308	79308	79308	78984	78984	78984

	(1) hlstat	(2) hlstat	(3) hlstat	(4) hlstat	(5) hlstat	(6) hlstat	(7) hlstat
TempMean	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SunDaily	-0.002**	-0.002**	-0.002**	-0.003**	-0.003***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RainDaily	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
WindSpeed	-0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hour of day	-	yes	yes	yes	yes	yes	yes
Day of week	-	-	yes	yes	yes	yes	yes
Month of year	-	-	-	yes	yes	yes	yes
Regional dummies	-	-	-	-	yes	yes	yes
Wave dummies	-	-	-	-	-	yes	yes
Individual level controls	-	-	-	-	-	-	yes
_cons	3.872***	3.858***	3.876***	3.884***	3.943***	4.049***	4.023***
	(0.008)	(0.016)	(0.018)	(0.020)	(0.043)	(0.048)	(0.064)
N	166673	165562	165562	165562	164707	164707	163865

Fixed effects with cluster standard errors. Individual level controls include gender, age, ethnicity, marriage, child, job status, household income and education indicators.