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Subjective wellbeing: why weather matters

John Feddersen,

University of Oxford, UK, and New York University, United Arab Emirates

Robert Metcalfe

University of Chicago, USA

and Mark Wooden

University of Melbourne, Australia

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Summary. The paper reports results from the first ever study of the effect of short-term weather and long-term climate on self-reported life satisfaction that uses longitudinal data. We find robust evidence that day-to-day weather variation impacts self-reported life satisfaction. Utilizing two sources of variation in the cognitive complexity of satisfaction questions, we present evidence that weather effects arise because of the cognitive challenge of reporting life satisfaction. We do not detect a relationship between long-term climate and self-reported life satisfaction by using an individual fixed effects specification, which identifies climate impacts through individuals moving location.

Keywords: Climate; Household, Income and Labour Dynamics in Australia Survey; Life satisfaction; Mood; Subjective wellbeing; Weather

1. Introduction

Social scientists increasingly turn to measures of subjective wellbeing, in addition to the traditional 'objective' measures of welfare such as gross domestic product, crime levels and health statistics, for welfare appraisal. Recent analysis uses subjective wellbeing measures to evaluate social progress (Stiglitz *et al*., 2009), value non-market goods (Welsch, 2006; Rehdanz and Maddison, 2008; Carroll *et al*., 2009; Frey *et al*., 2009; Luechinger, 2009; Levinson, 2012) and assess government policy (Diener *et al*., 2009; Dolan *et al*., 2011; Boarini *et al*., 2012; Dolan and Metcalfe, 2012). The value and importance of subjective wellbeing measures are increasingly recognized by governments (Diener *et al*., 2013). Measures of subjective wellbeing, for example, are central to the Organisation for Economic Co-operation and Development's new better life index (Organisation for Economic Co-operation and Development, 2011) and are now regularly collected by some national statistical agencies (notably the UK Office for National Statistics).

Nevertheless, scepticism about the usefulness of such subjective measures remains. One source of such scepticism is concerns that responses are biased by transient influences which, unless explicitly accounted for, can render such measures of little use for describing long-term trends in overall population wellbeing. An example of such an influence is weather on the day that the subjective wellbeing data are collected. In a much cited experimental study, involving a very

Address for correspondence: John Feddersen, Department of Economics and Smith School of Enterprise and the Environment, University of Oxford, Manor Road, Oxford, OX1 3UQ, UK.
E-mail: john.feddersen@economics.ox.ac.uk

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small non-random sample (84 respondents to a telephone survey of numbers chosen from a university student directory), Schwarz and Clore (1983) reported, in the absence of any priming about the weather on the day of interview, very large differences in the mean self-reported life satisfaction of respondents interviewed on a sunny day (a mean of 6.57 on a 1–10 scale) and those interviewed on a rainy day (a mean of 4.86). They speculated that weather affects mood (for further evidence see Keller *et al.* (2005) and Denissen *et al.* (2008)), which is one of several transient factors that respondents reflect on when expressing their self-reported life satisfaction.

Recently a small number of studies have revisited the issue of weather effects on subjective wellbeing, which, in contrast with Schwarz and Clore (1983), employ large population-representative data sets (either for the USA or Canada). Although results are mixed, none report weather effects of the magnitude that were reported by Schwarz and Clore (1983). Connolly (2013) found a significant negative effect of more precipitation and higher temperature, whereas Levinson (2012) found no effect of precipitation and a positive (though declining) effect of temperature on self-reported life satisfaction. Barrington-Leigh (2008) found that self-reported life satisfaction varies significantly with the amount of recent cloud cover. Finally, Lucas and Lawless (2013) found little evidence of a relationship between any of a large number of weather variables and self-reported life satisfaction.

This paper adds to this small literature. Specifically we use panel survey data following a representative sample of the Australian population which is then linked to Bureau of Meteorology data based on both place of residence and time of interview.

The innovative contributions of this paper are at least fourfold. First, and most importantly, it is the first paper in this literature to use panel data, and hence able to include individual fixed effects while estimating the effect of weather on self-reported life satisfaction. Recent psychology and economics literature has found that fixed person-specific traits are enormously important predictors of general satisfaction (Argyle, 1999; Diener and Lucas, 1999; Ferrer-i Carbonell and Frijters, 2004). As a consequence, a failure to control for this very large source of cross-person variation in self-reported life satisfaction has substantial potential to create omitted variable bias in estimates of the effect of weather on self-reported life satisfaction.

Second, Barrington-Leigh (2008), Connolly (2013), Levinson (2012) and Lucas and Lawless (2013) used weather variables for the day of, rather than at the precise time of, collection of self-reported life satisfaction data. Using a time marker for the start of the survey in which self-reported life satisfaction data are collected, we can use weather data at almost precisely the time of interview. Previous studies that found small and insignificant weather effects may simply have too much noise in the regressors and more specific measurement of weather conditions at the time of the interview will improve efficiency and remove downward bias.

Third, previous studies have typically focused on a small set of weather variables. Connolly (2013) and Levinson (2012) considered precipitation and temperature variables and Barrington-Leigh (2008) included cloud cover in addition. We consider these variables in addition to barometric pressure, wind speed and relative humidity, which have all been shown to influence mood or behaviour (Frijters and Van Praag, 1998; Keller *et al.*, 2005; Denissen *et al.*, 2008). These six weather variables are described by biometeorologists as providing 'the complete weather picture' (San-Gil *et al.* (1991), page 402). Because weather variables tend to be correlated, considering all weather variables together is important when evaluating which actually matter.

Fourth, our weather data are very spatially detailed, removing another potential source of noise in the regressors, when compared with previous studies. Almost all weather variables are collected from within 20 km of the survey location, with the mean distance from the location of collection of self-reported life satisfaction data to the nearest weather station being 8.9 km.

The values for the 10th, 50th and 90th percentiles of this distance are 2.45 km, 6.76 km and 17.26 km respectively.

With these enhancements, the first main finding of the paper is the significant weather effects that we estimate. Using ordinary least squares regression with individual fixed effects, we find a positive and statistically significant effect of global solar exposure, which provides a precise and spatially detailed measure of cloudiness. Additionally, we find negative and significant effects of barometric pressure and wind speed. Wind direction is also found to affect self-reported life satisfaction.

The second main contribution of the paper is evidence supporting the hypothesis that the cognitive complexity of assessing life satisfaction causes weather bias. To do this we make two assumptions—supported both theoretically and empirically—giving rise to variation in cognitive complexity of satisfaction questions. First, we consider the effect of weather on nine 'domain-specific' measures of wellbeing, which we assume are cognitively simpler to report than the 'domain-free' self-reported life satisfaction measure (Strack *et al.*, 1991). We find almost no significant weather effects for all these variables, suggesting that less cognitively complex questions suffer less from weather bias. Second, on the basis of evidence of 'panel conditioning' in the Household, Income and Labour Dynamics in Australia (HILDA) Survey as well as other life satisfaction surveys, we assume that the cognitive complexity of the life satisfaction question declines with experience. We show that weather bias declines with panel experience and therefore cognitive complexity.

The remainder of the paper proceeds as follows. Section 2 describes the econometric framework that is used and construction of the data set. Section 3 presents results. Section 4 concludes the paper.

2. Econometric framework and data

2.1. Econometric framework

We estimate the marginal effects of the variables of interest on subjective wellbeing, which is a proxy for actual wellbeing. Adopting a reduced form specification, we estimate the following linear regression model by ordinary least squares:

$$\mathrm{SWB}_{ijt} = \alpha_i + \alpha_j + \alpha_m + \alpha_y + W'_{jt}\beta + X'_{it}\gamma + \varepsilon_{ijt}. \quad (1)$$

Before estimating this we conducted a Hausman test of the appropriateness of a random-effects specification, rejecting the hypothesis that unobserved individual traits are not correlated with the explanatory variables. SWB_{ijt} is the stated life satisfaction of respondent i in location j at time t, where time is expressed in terms of the year, month, day and hour of interview, and α_i, α_j, α_m and α_y are dummy variables for individual, location (measured by postcode), month and year.

The use of individual fixed effects to control for omitted variable bias is a key contribution of this paper. Because unmeasurable individual characteristics are important determinants of self-reported life satisfaction (Argyle, 1999; Diener and Lucas, 1999) the scope for omitted variable bias in their absence is large. Indeed, with our self-reported life satisfaction data the R^2 of an ordinary least squares regression fitting only individual-specific dummy variables as independent variables is 0.6. Throughout this paper we report within-R^2-values.

As one example of a source of omitted variable bias consider 'active' people, who tend to be both more satisfied with life than average and busier than average when the sun is shining, and therefore tend not to be available to answer surveys in sunny conditions. These satisfied active

people are likely to be underrepresented in sunny weather conditions. Our results show that this is an important innovation.

Year dummies are assigned according to the HILDA Survey year, which starts in August, to control for wave-specific factors from the HILDA Survey as well as other year-specific factors. Month fixed effects control for seasonal variation in self-reported life satisfaction, and their inclusion eliminates confounding of weather at the time of interview with seasonal factors. For example, in the absence of month fixed effects, a positive effect of temperature on self-reported life satisfaction could either be caused by summer-specific factors or by the daily weather itself. Location fixed effects address a similar confounding problem between daily weather variables and climate—which is calculated as an annual average over 10 years—rather than season.

We include weather variables corresponding to the time and location of the interview, denoted by W_{jt}. These are the main variables of interest and the selection and construction of these is explained in detail in Section 2.2. In Section 3.3, to estimate climate effects, we include climate variables in our specification and remove postcode fixed effects.

We also include individual time-specific controls X_{it}. These include age and its square, the number of household dependents aged between 0 and 24 years, and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. These controls are typically the most important determinants of self-reported life satisfaction (Frijters *et al*., 2004).

Finally, X_{it} contains variables that enable us to investigate three other non-weather sources of potential bias. On the basis of Csikszentmihalyi and Hunter (2003) we include a dummy variable indicating whether the interview was conducted on a weekend and a variable measuring the hour of day at which the interview was conducted. Controlling for hour of day serves a second purpose; because four weather variables are measured at the time of the interview, absence of the hour variable would cause weather variables like temperature, which changes predictably throughout the day, to be confounded with effects that are related to the time of day, such as tiredness. Finally, following Wooden *et al*. (2009), we include an indicator variable which is equal to 1 if another person is present during the interview.

We use the Stata software package for all statistical analysis. Unless otherwise stated, we cluster our errors at the individual level to avoid overstating the precision of our point estimates because of a failure to incorporate within-individual correlations in the dependent variable (typically self-reported life satisfaction).

Arguably weights could be used to adjust for potential biases arising from non-random non-response. However, re-estimating equation (1) with weighted least squares, accepting the longitudinal weights provided with the HILDA Survey data, does not materially affect results. Given this immateriality, we believe that ordinary least squares provides a more transparent approach.

2.2. Data

Two sources are used in the construction of the data set. All non-weather variables are obtained from the HILDA Survey, whereas weather variables are extracted from the Australian Bureau of Meteorology (BOM) database.

2.2.1. Household, Income and Labour Dynamics in Australia Survey

The wellbeing data that are used in this study are drawn from waves 1–9 of the HILDA Survey. Described in more detail in Wooden and Watson (2007), the HILDA Survey is an unbalanced

household panel survey with a focus on work, income and family. Its design is closely modelled on the British Household Panel Survey and the German Socio-Economic Panel.

The survey began in 2001 with a national probability sample of Australian households. Personal interviews were completed at 7682 households in wave 1, and these generated a responding sample of 13 969 individuals. The characteristics of the sample match the broader adult population quite well.

The members of these participating households form the basis of the panel that is pursued in the subsequent waves of interviews, which are conducted approximately 1 year apart. Interviews are conducted with all adults (defined as people aged 15 years or older on June 30th preceding the interview date) who are members of the original sample, as well as any other adults who, in later waves, are residing with an original sample member. Annual reinterview rates (the proportion of respondents from one wave who are successfully interviewed the next) are reasonably high, rising from 87% in wave 2 to 96.3% in wave 9.

The main outcome variable that is used in this analysis is a measure of overall life satisfaction. It is constructed from responses to a single item scored on an 11-point scale ranging from 0 to 10. Single-item life satisfaction questions are the most commonly used measure of subjective wellbeing by economists (Dolan *et al.*, 2008). The question, which is delivered by an interviewer, either in person or by telephone is 'All things considered, how satisfied are you with your life?'. A score of 0 is labelled and described as 'totally dissatisfied' and a score of 10 labelled and described as 'totally satisfied'. This question is almost identical to a question that is included every year in the German Socio-Economic Panel and is similar to those in cross-country surveys, such as the World Values Survey and the Euro-Barometer Survey. It is also very similar to the question that was used in Schwarz and Clore's (1983) seminal work, asking 'How satisfied are you with your life as a whole these days?'.

We also consider the effect of weather variables on satisfaction with job, employment opportunities, financial situation, home, local community, neighbourhood, safety, health and free time, which are similarly scaled from 0 to 10. Finally, the HILDA Survey also provides the controls for age, number of household dependents, the natural logarithm of nominal household equivalized disposable income, disability status, employment status, relationship status, highest level of education and gender. Summary statistics for all HILDA Survey variables used are presented in Table 1. Detailed descriptions of all variables are in Tables 2 and 3. 309 observations of income take the value 0 so we add 1 to each value before taking the logarithm. 440 observations report negative real household equivalized disposable income and these are dropped from the sample.

For our purposes, one advantage of using data from the HILDA Survey, rather than the British Household Panel Survey and German Socio-Economic Panel, is the spread of weather conditions in Australia. We can consider weather and climate effects in many highly heterogeneous locations. Because interviews are conducted between August and February, we can also consider weather effects in different seasons. It seems plausible that self-reported life satisfaction would, for example, exhibit a positive weather influence of both warm temperatures in winter and cool temperatures in summer.

A second advantage over other sources of data on self-reported life satisfaction arises because the data set contains information on survey start time. This allows weather data to be matched very precisely to the time of interview.

2.2.2. *Bureau of Meteorology*

Weather data are obtained from the BOM and, to identify the relative contribution of similar weather types, we choose to include a broad selection of the available weather variables. For example, estimating the effect of temperature on self-reported life satisfaction in a model that

Table 1. Summary of variables

Variable	Observations	Mean	Standard deviation	Minimum	Maximum	Source
Satisfaction—life	116017	7.91	1.52	0	10	HILDA
Satisfaction—job overall	73853	7.65	1.75	0	10	HILDA
Satisfaction—employment opportunities	90941	7.00	2.43	0	10	HILDA
Satisfaction—financial situation	116013	6.37	2.31	0	10	HILDA
Satisfaction—home in which you live	116006	7.96	1.89	0	10	HILDA
Satisfaction—feel part of local community	115981	6.74	2.23	0	10	HILDA
Satisfaction—neighbourhood in which you live	116005	7.91	1.78	0	10	HILDA
Satisfaction—how safe you feel	116015	8.10	1.70	0	10	HILDA
Satisfaction—your health	116048	7.34	1.99	0	10	HILDA
Satisfaction—amount of free time	115991	6.66	2.57	0	10	HILDA
Age	116103	43.80	18.30	15	101	HILDA
Household dependents	116103	0.64	1.08	0	10	HILDA
Household equivalized income	116103	34528	25694	0	1132686	HILDA
Mild disability (dummy)	116103	0.08	0.27	0	1	HILDA
Moderate disability (dummy)	116103	0.17	0.37	0	1	HILDA
Severe disability (dummy)	116103	0.01	0.09	0	1	HILDA
Unemployed (dummy)	116103	0.04	0.18	0	1	HILDA
Not in labour force (dummy)	116103	0.33	0.47	0	1	HILDA
Married (dummy)	116072	0.50	0.50	0	1	HILDA
Defacto (dummy)	116072	0.12	0.33	0	1	HILDA
Separated (dummy)	116072	0.03	0.17	0	1	HILDA
Divorced (dummy)	116072	0.06	0.24	0	1	HILDA
Widowed (dummy)	116072	0.05	0.22	0	1	HILDA
Postgrad (dummy)	116103	0.03	0.17	0	1	HILDA
Graduate diploma or certificate (dummy)	116103	0.05	0.21	0	1	HILDA
Bachelor (dummy)	116103	0.12	0.32	0	1	HILDA
Diploma (dummy)	116103	0.08	0.28	0	1	HILDA
Certificate 3/4 (dummy)	116103	0.19	0.39	0	1	HILDA
Certificate 1/2 (dummy)	116103	0.01	0.12	0	1	HILDA
Certificate unknown (dummy)	116103	0.01	0.08	0	1	HILDA
Year 12 (dummy)	116103	0.15	0.36	0	1	HILDA
Other present (dummy)	116103	0.37	0.48	0	1	HILDA
Male (dummy)	116103	0.47	0.50	0	1	HILDA
Hour	116103	15.26	3.61	3	24	HILDA
Weekend (dummy)	116103	0.26	0.44	0	1	HILDA

(*continued*)

Table 1 (*continued*)

Variable	*Observations*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*	*Source*
Solar exposure	112488	19.29	6.43	0.22	35.29	BOM
Precipitation	115434	1.75	5.40	0	175.75	BOM
Wind speed (daily mean)	115405	3.94	1.91	0	19.05	BOM
Mean sea level pressure	100029	1016.03	7.08	979.72	1039.16	BOM
Temperature	113595	18.20	5.60	−2.90	45.29	BOM
Relative humidity	112849	62.39	20.03	1.12	100	BOM
Wind direction (north)	116103	0.20	0.40	0	1	BOM
Wind direction (east)	116103	0.23	0.42	0	1	BOM
Wind direction (west)	116103	0.29	0.45	0	1	BOM
Wind speed	113108	4.87	2.43	0	21.81	BOM
Daily solar exposure (monthly average)	116103	19.36	3.70	8.01	30.53	BOM
Precipitation (monthly average)	116103	54.09	25.76	0.14	517.14	BOM
Mean daily wind speed (monthly average)	116103	3.88	0.97	0.24	9.01	BOM
Maximum daily temperature (monthly average)	116103	21.74	4.21	5.40	38.62	BOM
Daily solar exposure (annual average)	116103	18.69	2.02	13.58	30.17	BOM
Precipitation (annual average)	116103	773.56	312.94	116.60	3340.30	BOM
Mean daily wind speed (annual average)	116103	3.63	0.96	0.85	7.59	BOM
Maximum daily temperature (annual average)	116103	22.87	2.98	10.22	34.90	BOM

Table 2. Variable descriptions (I)

Variable	*Description*
Weather	
Solar exposure	Global solar exposure is the total amount of solar energy falling on a horizontal surface: the daily global solar exposure is the total solar energy for a day; typical values for daily global solar exposure range from 1 to 35 MJ m^{-2}; the values are usually highest in clear sun conditions during the summer, and lowest during winter or very cloudy days; details of data collection are available from `http://www.bom.gov.au/climate/austmaps/metadata-daily-solar-exposure.shtml`
Precipitation	Precipitation in the 24 h before 9 a.m. (local time) in millimetres
Wind speed (daily mean)	Mean daily wind speed in metres per second
Mean sea level pressure	Mean sea level pressure in hectopascals
Temperature	Dew point temperature observation in degrees centigrade
Relative humidity	Relative humidity in percentage
Wind speed	Wind speed measured in metres per second
Wind direction (north)	Indicator variable equal to 1 if the wind direction is greater than 315° and less than 45°
Wind direction (east)	Indicator variable equal to 1 if the wind direction is greater than 45° and less than 135°
Wind direction (west)	Indicator variable equal to 1 if the wind direction is greater than 135° and less than 225°
Wind direction (south)	Indicator variable equal to 1 if the wind direction is greater than 225° and less than 315°
Other variables of interest	
Hour	Time of interview rounded to the nearest of 0300 h, 0600 h, 0900 h, 1200 h, 1500 h, 1800 h, 2100 h or 2400 h
Weekend	Indicator variable equal to 1 if the interview occurred on Saturday or Sunday
Other present	Indicator variable equal to 1 if the respondent answered yes to the following question: 'Were any other adults present during any of this interview?'
Controls—continuous	
Age	Age last birthday at June 30th in the year the survey wave begins
Household dependents	Number of dependent children aged 0–24 years
Household income	Nominal household equivalized income: calculated as household financial year disposable income divided by $1 +$ (number of adults 15 years and over-1) $\times$ $0.5 +$ number of dependents under 15 years $\times$ 0.3

does not control for solar exposure is likely to yield spurious results. First, we incorporate similar measures to past studies: precipitation, temperature and cloud cover (Barrington-Leigh, 2008; Connolly, 2013; Levinson, 2012; Lucas and Lawless, 2013). Past studies have also considered snow, which is very rare in Australian population centres.

We approximate cloudiness with global solar exposure, which is measured by satellite and is available for more locations than cloud coverage. Values of daily global solar exposure are highest in clear conditions and lowest on very cloudy days. BOM daily solar exposure gridded data sets cover Australia with a resolution of 0.05° in latitude and longitude (roughly 5 km^2). To these previously used variables we add three additional variables, which past studies suggest are important. These are barometric pressure (Keller *et al.*, 2005), relative humidity (Frijters and Van Praag, 1998) and wind speed (Denissen *et al.*, 2008). Together, these are the six most commonly reported weather variables by a significant margin. Summary statistics are again provided in Table 1, a correlation matrix for the weather variables is in Table 4 and a description of the weather variables is in Table 2.

Whenever possible, we use weather variables that were recorded at the time of the interview.

Table 3. Variable descriptions (II)

Control variables—indicators	*Description*
Disability (mild)	Respondent stated they had a long-term health condition, impairment or disability that restricts everyday activities and has lasted, or is likely to last, for 6 months or more and they stated that the long-term health condition had no effect on the type or amount of work done
Disability (moderate)	Respondent stated they had a long-term health condition, impairment or disability that restricts everyday activities and has lasted, or is likely to last, for 6 months or more and they stated that the long-term health condition impacts the type or amount of work done
Disability (severe)	Respondent stated they had a long-term health condition, impairment or disability that restricts everyday activities and has lasted, or is likely to last, for 6 months or more and they stated that the long-term health condition means that the respondent cannot work
Unemployed	Respondent stated their labour force status as unemployed
Not in labour force	Respondent stated their labour force status as not in the labour force
Employed	Respondent stated their labour force status as employed
Single	Respondent stated their marital status as never married and not *de facto*
Married	Respondent stated their marital status as married
Defacto	Respondent stated their marital status as *de facto*
Separated	Respondent stated their marital status as separated
Divorced	Respondent stated their marital status as divorced
Widowed	Respondent stated their marital status as widowed
Postgraduate	Respondent stated their highest education level achieved as Masters or doctorate
Graduate diploma or certificate	Respondent stated their highest education level achieved as graduate diploma or graduate certificate
Bachelor	Respondent stated their highest education level achieved as Bachelor or Honours
Diploma	Respondent stated their highest education level achieved as advanced diploma or diploma
Certificate 3/4	Respondent stated their highest education level achieved as certificate III or IV
Certificate 1/2	Respondent stated their highest education level achieved as certificate I or II
Certificate (unknown)	Respondent stated their highest education level achieved as certificate (not defined)
Year 12	Respondent stated their highest education level achieved as year 12
Year 11	Respondent stated their highest education level achieved as year 11

There are four interview time-specific weather variables—mean sea level pressure, temperature, wind speed and relative humidity—which are recorded at 3-h intervals throughout the day. Global solar exposure and precipitation are recorded daily and, because wind speed and direction tend to be correlated, in all models we also include dummy variables indicating the direction of the wind (north, south, east or west). Finally, as wind speed changes rapidly throughout the day, we include daily mean wind speed in addition to wind speed at the time of interview.

As a check of robustness, and to consider the effects of season and climate on self-reported life satisfaction, we also consider monthly and annual averages of global solar exposure, wind speed, daily maximum temperature and precipitation in our analysis. Monthly and annual averages for mean sea level pressure and relative humidity are not readily available from the BOM.

Weather variables are obtained from each of the weather stations in operation from January 2001 until the completion of wave 9 in 2010. Fig. 1 plots the location of all the stations that were used in this study. Over 90% of observations are within 20 km of the closest weather station.

Reported longitude and latitude of census collection districts (CDs) in the HILDA Survey data and of weather stations in the BOM data enable HILDA Survey responses to be matched to weather variables on the survey day. With 850 stations and HILDA Survey sample members

Table 4. Weather variable correlations

	Solar exposure	*Precipitation*	*Mean daily wind speed*	*Wind speed*	*Mean sea level pressure*	*Temperature*	*Relative humidity*
Solar exposure	1.00						
Precipitation	−0.22	1.00					
Mean daily wind speed	−0.11	0.14	1.00				
Wind speed	−0.01	0.08	0.70	1.00			
Mean sea level pressure	0.11	−0.10	−0.29	−0.29	1.00		
Temperature	0.49	−0.14	−0.11	0.08	−0.20	1.00	
Relative humidity	−0.35	0.18	−0.02	−0.09	0.02	−0.41	1.00

Fig. 1. Map of Australian BOM weather stations

spread across roughly 9000 CDs, each weather station may map to several CDs. Australia has approximately 37000 CDs in total, with roughly 225 dwellings in each.

We take two steps to match the data. First, we calculate the three closest weather stations to the CD of the household completing the HILDA Survey by great circle distance. Second, we take a simple distance-weighted average of the weather at these three stations to use for analysis. This method has the advantage of enabling interpolation between weather stations to measure the weather at a particular location better.

3. Results

3.1. Weather effects

3.1.1. Main results

In Table 5, we present three models: model 1 presents our baseline estimated weather effects for the full sample; model 2 contains only the weather variables and no controls; model 3 includes only the controls.

Weather clearly has a statistically significant effect on self-reported life satisfaction in our baseline model. In model 1, total daily solar exposure, mean sea level air pressure and the direction of the wind have significant coefficients. Specifically, higher solar exposure and lower air pressure, which is typically associated with clouds, rain and strong winds, increase self-

Table 5. Baseline estimates of weather's influence on life satisfaction†

	Model 1 coefficient	*Model 2 coefficient*	*Model 3 coefficient*
Weather—day of interview			
Solar exposure	0.00191‡	0.00175§	
Precipitation	0.000179	0.000382	
Wind speed (daily mean)	−0.00710§	−0.00813‡	
Weather—time of interview			
Mean sea level pressure	−0.00223§§	−0.00215§§	
Temperature	−0.00141	−0.00206	
Relative humidity	−0.000242	−0.000570‡	
Wind speed	0.00339	0.00346	
Wind direction (north)	0.0190	0.0203	
Wind direction (east)	0.0348§§	0.0346§§	
Wind direction (west)	0.00815	0.0107	
Other variables of interest			
Hour	−0.00496§§		−0.00452§§
Weekend	−0.00282		0.000747
Other present	0.0396§§		0.0391§§
Controls			
Age	−0.0372§§		−0.0366§§
Age squared	0.000182§§		0.000166§§
Household dependents	−0.0381§§		−0.0352§§
ln(household income)	0.0240§§		0.0275§§
Disability (mild)	−0.0553§§		−0.0537§§
Disability (moderate)	−0.238§§		−0.243§§
Disability (severe)	−0.460§§		−0.519§§
Unemployed	−0.203§§		−0.207§§
Not in labour force	−0.0362§		−0.0310
Married	0.277§§		0.267§§
Defacto	0.297§§		0.289§§
Separated	−0.398§§		−0.424§§
Divorced	−0.146‡		−0.158§§
Widowed	−0.126		−0.161‡
Postgraduate	−0.160		−0.132
Graduate diploma or certificate	−0.0828		−0.0879
Bachelor	−0.232§§		−0.223§§
Diploma	−0.211§§		−0.217§§
Certificate 3/4	−0.117‡		−0.137§§
Certificate 1/2	0.0723		0.0625
Certificate (unknown)	0.228		0.138
Year 12	−0.186§§		−0.200§§
Month fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
State fixed effects	No	No	No
Postcode fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
R^2 (within)	0.617	0.622	0.614
F-statistic (weather)	2.53	2.75	
F-statistic p-value	0.0048	0.0022	
N	96472	96493	115989

†Dependent variable: life satisfaction; individual clustered standard errors of the mean are in parentheses. See Tables 2 and 3 for detailed descriptions of the variables.
‡Significant at the 0.05 level.
§Significant at the 0.1 level.
§§Significant at the 0.01 level.

reported life satisfaction. The positive and significant coefficient on the dummy for east-directed wind is less intuitive. It seems unlikely that this result will hold in all locations, and we speculate that this is a consequence of the significant population concentration on the east coast of Australia. We interpret this result as suggesting that wind direction is a source of bias in self-reported life satisfaction measures, but that the strength and direction of the effect depend on local factors. Neither temperature nor precipitation coefficients are significant in model 1, suggesting that our new variables, solar exposure and sea level pressure, are more important than those traditionally used to evaluate the effect of weather on self-reported life satisfaction. An F-statistic for the joint significance of the weather variables is reported in all the tables in this paper and for model 1 the hypothesis that weather has no influence on self-reported life satisfaction is strongly rejected.

Considering the size of the effects in model 1, if total daily solar exposure is 1 standard deviation (6.43 $\mathrm{MJ\,m^{-2}}$) above average, we estimate that self-reported life satisfaction is 0.012 points higher. A 1-standard-deviation decrease in mean sea level pressure (7.08 hPa) increases self-reported life satisfaction in our model by 0.016 and a 1-standard-deviation decrease in wind speed (1.91 $\mathrm{m\,s^{-1}}$) increases self-reported life satisfaction by 0.014.

How large are these effects? It is informative to compare these effects with non-weather coefficients in model 1. Though the magnitude of these effects may be judged small, to place these magnitudes into context first note that there is a substantial component of subjective wellbeing that is stable over time, due in part to personality traits and other factors that are inherited (Lykken and Tellegen, 1996). As a result, even very large changes in circumstances tend not to change self-reported life satisfaction by even 1 unit. Weather coefficients are small relative to becoming unemployed from employed (−0.203), acquiring a severely disability (−0.460) or separating from a partner (−0.398). However, common day-to-day changes in weather influence self-reported life satisfaction by similar orders of magnitude to acquiring a mild disability (−0.0553) and leaving the labour force having been employed (−0.0362). To a first-order approximation, a 10% increase in household nominal equivalized income is associated with a relatively modest increase in self-reported life satisfaction of 0.0024, meaning that commonly observed day-to-day weather variation has an effect on self-reported life satisfaction that dwarfs even very large changes in income.

The existence of significant coefficients is of theoretical interest; however, the practical importance of the bias deserves mention. This is clear from consideration of model 2, which contains only weather variables, and model 3, which contains only the controls. Most importantly, the inclusion of weather controls does not appear to alter the non-weather coefficients much. The 'widowed' coefficient is no longer significant once weather variables have been included in the regression; however, this is unusual and coefficients mostly change by less than 10%. Subjective wellbeing studies that do not control for weather do not appear to be materially biased.

Comparing models 1 and 2, the significant coefficients are somewhat different (especially the coefficient on relative humidity), highlighting the importance of controlling for individual-specific factors when estimating the effect of weather on self-reported life satisfaction.

The omission of weather does not appear to influence non-weather variables substantially in this study. However, given the rapidly expanding uses of subjective wellbeing data, situations may arise where weather controls reduce bias substantially. For example, as Levinson (2012) noted, wind speed and air quality are correlated and any study attempting to estimate the effect of air pollution on self-reported life satisfaction must account for wind, or risk capturing the weather effects in their estimation. Wind controls have typically not been adopted in past studies of air pollution effects. Alternatively, studies considering the effect of once-off events on self-reported life satisfaction (Kavetsos and Szymanski, 2010; Metcalfe *et al.*, 2011) should

take measures to ensure that changes in the weather before and after the event do not drive the observed changes in subjective wellbeing.

The inclusion of individual fixed effects is a vital innovation of this paper. Table 6 presents estimates of weather effects with and without individual fixed effects. Model 4 incorporates month and wave fixed effects only, whereas model 5 includes state fixed effects also. These specifications are included to replicate the approach in a recent analysis of US data by Connolly (2013) and help to illustrate the importance of adopting individual and postcode fixed effects (as in model 1 in Table 5). Like Connolly (2013), models 4 and 5 detect a significant effect of temperature on self-reported life satisfaction; warmer weather reduces self-reported life satisfaction. We also find that higher sea level air pressure causes disutility and that the direction of the wind matters.

Time invariant postcode level heterogeneity is likely to be important in light of the literature on the relationship between climate variables (i.e. long-run weather averages) and self-reported life satisfaction (Frijters and Van Praag, 1998; Rehdanz and Maddison, 2005; Brereton *et al.*, 2008). In the absence of a control for this, short-term weather and long-term climate are confounded such that it is not possible to isolate the weather effect. For example, a positive coefficient on temperature may arise because people in warm places have higher self-reported life satisfaction, even if transient weather has no effect on self-reported life satisfaction. In model 6 we include postcode level fixed effects to address this empirical challenge and find that coefficients on solar exposure, temperature and humidity are no longer significant.

Model 7, which replicates model 1 in Table 5, but is reproduced for ease of comparison, also controls for time invariant individual-specific heterogeneity. The increase in the R^2-term from 0.14 to 0.62 with individual fixed effects supports previous literature showing that unobserved individual-specific factors are among the most important predictors of self-reported life satisfaction and this suggests that the scope for omitted variable bias is significantly reduced in model 1 (and model 7).

Finally, three non-weather coefficients are of note as potential sources of bias. Self-reported life satisfaction declines throughout the day: a 10-h difference in interview time resulting in a roughly 0.05-unit decrease in self-reported life satisfaction. The coefficient on the variable indicating whether another person was present during the interview increases self-reported life satisfaction by approximately 0.04 units. As in Csikszentmihalyi and Hunter (2003) and Kahneman and Deaton (2010), we initially find evidence (in models 4, 5 and 6) that interviews on the weekend influence self-reported life satisfaction. However, the effect disappears with individual fixed effects.

3.1.2. Sensitivity analysis and robustness checks

We next turn to the question of whether heterogeneous weather effects arise across genders, seasons, locations and lags of weather variables. Such effects have been identified by both Connolly (2013) and Lucas and Lawless (2013). Connolly (2013) found that females are typically more responsive to weather variables, whereas Lucas and Lawless (2013) found a small heterogeneous effect depending on the season. Table 7 displays results when model 1 is estimated for male and female respondents separately. For males, the two key variables are total daily global solar exposure and mean sea level air pressure. Wind speed is not significant, either at the time of the interview or the daily average; nor are relative humidity, temperature and the direction of the wind.

The results for females are all in the same direction as for males, but the significant variables are different. Female response to solar exposure and sea level air pressure are respectively roughly a third and 70% that of males and neither is found to be significantly different from 0. Female self-reported life satisfaction is more responsive to wind speed than that of males and wind direction appears to play a similarly significant role across genders.

Table 6. Estimating the importance of weather controls†

	Model 4 coefficient	*t-statistic*	*Model 5 coefficient*	*t-statistic*	*Model 6 coefficient*	*t-statistic*	*Model 7 coefficient*	*t-statistic*
Weather—day of interview								
Solar exposure	0.00359‡	(3.46)	0.00398‡	(3.88)	0.00112	(1.14)	0.00191§	(2.11)
Precipitation	−0.0000168	(−0.02)	−0.0000950	(−0.10)	0.000247	(0.26)	0.000179	(0.21)
Wind speed (daily mean)	0.000808	(0.18)	0.00182	(0.41)	−0.0123‡	(−3.05)	−0.00710§§	(−1.90)
Weather—time of interview								
Mean sea level pressure	−0.00326‡	(−3.77)	−0.00287‡	(−3.40)	−0.00295‡	(−3.62)	−0.00223‡	(−2.97)
Temperature	−0.00310§§	(−1.92)	−0.00357§	(−2.13)	−0.00242	(−1.57)	−0.00141	(−0.99)
Relative humidity	0.000938§	(2.53)	0.000922§	(2.46)	−0.000570§	(−1.98)	−0.000242	(−0.77)
Wind speed	0.00441	(1.46)	0.00455	(1.51)	0.00567§§	(1.94)	0.00339	(1.29)
Wind direction (north)	0.0405‡	(2.65)	0.0339§	(2.24)	0.0198	(1.37)	0.0190	(1.41)
Wind direction (east)	0.0355§	(2.50)	0.0271§§	(1.93)	0.0224	(1.64)	0.0348‡	(2.76)
Wind direction (west)	0.0114	(0.83)	0.0137	(1.00)	0.0123	(0.94)	0.00815	(0.67)
Other variables of interest								
Hour	−0.00936‡	(−4.92)	−0.00917‡	(−4.82)	−0.00501‡	(−2.73)	−0.00496‡	(−3.09)
Weekend	−0.0482‡	(−3.73)	−0.0471‡	(−3.64)	−0.0514‡	(−4.08)	−0.00282	(−0.25)
Other present	0.0877‡	(6.70)	0.0880‡	(6.71)	0.0788‡	(6.19)	0.0396‡	(3.66)
Month fixed effects	Yes		Yes		Yes		Yes	
Wave fixed effects	Yes		Yes		Yes		Yes	
State fixed effects	No		Yes		No		No	
Postcode fixed effects	No		No		Yes		Yes	
Individual fixed effects	No		No		No		Yes	
R^2 (within)	0.0941		0.0944		0.143		0.622	
F-statistic (weather)	4.47		4.39		2.51		2.53	
F-statistic p-value	0.0000		0.0000		0.0052		0.0048	
N	96472		96472		96472		96472	

†Individual clustered standard errors of the mean are in parentheses. The dependent variable is life satisfaction from waves 1–9 of the HILDA Survey. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed variable descriptions.
‡Significant at the 0.01 level.
§Significant at the 0.05 level.
§§Significant at the 0.1 level.

Table 7. Examining the effect of gender†

	Model 8—male coefficient	*t-statistic*	*Model 9—female coefficient*	*t-statistic*
Weather—day of interview				
Solar exposure	0.00292‡	(2.27)	0.00102	(0.79)
Precipitation	−0.000258	(−0.21)	0.000643	(0.56)
Wind speed (daily mean)	0.0000226	(0.00)	−0.0134§	(−2.58)
Weather—time of interview				
Mean sea level pressure	−0.00266‡	(−2.44)	−0.00176§§	(−1.68)
Temperature	−0.00120	(−0.61)	−0.00121	(−0.59)
Relative humidity	−0.000501	(−1.09)	0.0000146	(0.03)
Wind speed	0.00227	(0.59)	0.00447	(1.21)
Wind direction (north)	0.0168	(0.87)	0.0229	(1.23)
Wind direction (east)	0.0380‡	(2.06)	0.0348‡	(1.99)
Wind direction (west)	−0.00473	(−0.26)	0.0189	(1.14)
Other variables of interest				
Hour	−0.00546‡	(−2.35)	−0.00474‡	(−2.11)
Weekend	−0.00568	(−0.34)	−0.00429	(−0.27)
Other present	0.0380‡	(2.50)	0.0450§	(2.89)
Month fixed effects	Yes		Yes	
Wave fixed effects	Yes		Yes	
Postcode fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
R^2 (within)	0.646		0.616	
F-statistic (weather)	2.11		1.4	
F-statistic p-value	0.0203		0.1737	
N	45598		50874	

†Dependent variable: life satisfaction; individual clustered standard errors of the mean are in parentheses. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed descriptions of the variables.
‡Significant at the 0.05 level.
§Significant at the 0.01 level.
§§Significant at the 0.1 level.

The results tables underpinning the sensitivity analysis that is discussed in the remainder of this section can be found in the on-line supplementary tables to this paper. Climate and season interactions are less pronounced than expected. Our prior had been that many weather variables would have opposite effects in warm and cold climates or months. We find that coefficients on those variables that are significant for the whole sample do not change sign across the seasons. In one respect these results are not surprising: whereas weather can be either too hot or too cold, those variables that we find to be significant—solar exposure and mean sea level pressure—do not have an obvious optimal level.

We find no evidence of non-linear effects through either ‘extreme’ weather (weather below the fifth percentile and above the 95th percentile for all observations) or the inclusion of squared weather terms in our analysis. These results also suggest that rare extreme weather events do not drive our estimated weather effects.

We also consider the effect of lagged weather variables, both 3 h and 6 h before the survey

begins. We find some evidence that a change in wind speed matters, with high wind speed 6 h before the interview and low wind speed at the time of interview increasing self-reported life satisfaction.

Table 8 presents six additional robustness tests. The inclusion of interviewer fixed effects in model 10 does not materially affect our results. This addresses the potential concern that the weather effects that we estimate actually arise from the influence of specific interviewers on responses. For example, if a given interviewer conducted all her interviews for a given time period in a given place this might bias results. This appears to be of no concern, however, as models with interviewer fixed effects yield very similar results to those without.

Models 11, 12 and 13 show that this paper's key results are robust to error clustering at the interviewer, postcode and census CD levels; indeed, results tend to be more statistically significant under such specifications. Model 14 presents results by using a least squares approach weighted according to the appropriate population weights from the HILDA Survey data. This specification addresses the relatively small extent to which the HILDA data may not be representative of the Australian population.

3.1.3. Interpretation

Our results are different from, yet not inconsistent with, the results of Barrington-Leigh (2008), Connolly (2013), Levinson (2012) and Lucas and Lawless (2013). We believe that this is mainly a consequence of four novel aspects of our study. First, we use panel data and Table 6 shows that the absence of individual fixed effects yields a significant temperature effect that is similar to Connolly (2013). Second, by including more variables we can detect new relationships. For example, we detect a highly significant coefficient on air pressure, which is a variable that past studies have not considered. These additional variables may also explain why we find no significant effects of precipitation, which may have been a proxy for air pressure in past studies. Finally, we believe that the temporal and spatial accuracy of our data removes downward bias in the coefficients on weather variables. This may explain why we find significant weather effects where Lucas and Lawless (2013) found none.

Coefficients on solar exposure and wind speed in model 1 are consistent with most common theoretical priors. There is a well-documented link between sunlight and levels of the mood regulating neurotransmitter serotonin. Sunniness and cloudiness were also the original weather variables hypothesized by Schwarz and Clore (1983) to influence self-reported life satisfaction. Less obvious is why sunshine matters for males and not females. Without speculating why, we note that gender differences in self-reported life satisfaction influences are extremely common. Wind speed, especially gusty conditions, may be unsettling to respondents and the fact that wind is more important for female self-reported life satisfaction appeals to gender stereotypes. Females may be more likely to dress or groom in a way that is more adversely affected by wind.

The strongly significant coefficient on air pressure is more difficult to reconcile with intuition. Low air pressure is associated with inclement weather and Table 4 indicates that its strongest correlations are with wind speed and temperature. Internet searching yields enormous anecdotal and quasi-academic literatures on the relationship between air pressure and pain without robust unifying conclusions. One of the more reputable sources is the Swiss Department of Meteorology and Climatology, which found no clear evidence on how pressure affects people (`http://www.meteosuisse.admin.ch`). The notion that changes in air pressure cause pain is among the most common and we have considered changes in pressure 3 and 6 h before interview in Table 4 in the on-line supplementary tables to this paper and found no significant effects. We refrain from speculating further on the causes, noting that it is among the most robust weather influences that we find, and that its mechanism deserves further empirical attention.

Table 8. Robustness checks†

	Model 10 coefficient	*Model 11 coefficient*	*Model 12 coefficient*	*Model 13 coefficient*	*Model 14 coefficient*	*Model 15 coefficient*
Specification	Interviewer fixed effects	Clustered errors (interviewer)	Clustered errors (postcode)	Clustered errors (census CD)	Weighted least squares	Working hour controls
Weather—day of interview						
Solar exposure	0.00216‡	0.00191‡	0.00191‡	0.00191‡	0.00189§	0.00194‡
Precipitation	0.000448	0.000179	0.000179	0.000179	0.00063	0.000171
Wind speed (daily mean)	−0.00690§	−0.00710§	−0.00710‡	−0.00710‡	−0.00444	−0.00700§
Weather—time of interview						
Mean sea level pressure	−0.00249§§	−0.00223§§	−0.00223§§	−0.00223§§	−0.00192‡	−0.00223§§
Temperature	−0.00159	−0.00141	−0.00141	−0.00141	−0.000384	−0.00145
Relative humidity	−0.00027	−0.000242	−0.000242	−0.000242	−0.0000617	−0.000238
Wind speed (daily mean)	0.00346	0.00339	0.00339	0.00339	0.00215	0.0032
Wind direction (north)	0.0159	0.019	0.019	0.019	0.00786	0.0194
Wind direction (east)	0.0355§§	0.0348§§	0.0348§§	0.0348§§	0.0331‡	0.0348§§
Wind direction (west)	0.00724	0.00815	0.00815	0.00815	0.00919	0.00836
Other variables of interest						
Other present	0.0492§§	0.0396§§	0.0396§§	0.0396§§	0.0374§§	0.0390§§
Hour	−0.00474§§	−0.00496§§	−0.00496§§	−0.00496§§	−0.00448‡	−0.00472§§
Weekend	−0.00508	−0.00282	−0.00282	−0.00282	0.00849	−0.00101
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Postcode fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Interviewer	Yes	No	No	No	No	No
R^2 (within)	0.626	0.622	0.622	0.622	0.631	0.622
N	96472	96472	96472	96472	95884	96472

†Clustered standard errors are at the individual level unless otherwise specified. The dependent variable is life satisfaction from waves 1–9 of the HILDA Survey. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed variable descriptions.
‡Significant at the 0.05 level.
§Significant at the 0.1 level.
§§Significant at the 0.01 level.

Finally, we put forward two potential explanations for the hour-of-day effect. First, those answering the question later in the day may exhibit 'grumpiness' at having to fill out a survey in the evening. Second, responses later in the day may reflect tiredness, which may be associated with a decrease in perceived self-reported life satisfaction. We can address the possibility that those who are interviewed later in the day may be working longer hours, impacting self-reported life satisfaction (surveys are rarely conducted at the workplace). The addition of controls for the number of hours worked per week, however, made little difference to the hour-of-day effect, suggesting that this explanation can be rejected. These results are presented in model 15 of Table 8.

3.2. Cognitive complexity and weather bias

3.2.1. Domain-specific satisfaction

Strack *et al.* (1991) were among the first to suggest that the complexity of the task of evaluating one's life satisfaction may lead respondents to use heuristics, such as one's mood at the time, when reporting life satisfaction. This can introduce effects of transient variables such as weather. They noted (at page 39) that

> 'Evaluations of general life satisfaction pose an extremely complex task that requires a large number of comparisons along many dimensions with ill-defined criteria and the subsequent integration of the results of these comparisons into one composite judgment ... evaluations of specific domains, on the other hand, are often less complex. In contrast to judgments of general life satisfaction, comparison information is usually available for judgments of specific life domains and criteria for evaluation are well-defined.'

For example, Schwarz *et al.* (1987) demonstrated an effect of the German national football team's performance on self-reported life satisfaction but not satisfaction with work or income. In this section we test whether our weather variables influence a series of domain-specific measures of subjective wellbeing. First, we make explicit the assumption that is required to conduct this test.

Assumption 1. Domain-specific satisfaction is cognitively less complex to report than domain-free satisfaction.

Table 9 presents the results of estimating equation (1) after replacing the outcome variable with self-reported measures of satisfaction with job, employment opportunities, personal financial situation, the home, local community, local neighbourhood, safety, health and free time. Strikingly, in light of the significant influence of weather variables, both individually and jointly on self-reported life satisfaction, we find that in all nine domain-specific models the weather variables are never jointly significant, even at the 10% level. Of the 90 weather coefficients that were estimated, three are significant at the 5% level and eight are significant at the 10% level. This is slightly less significance than one would expect randomly, further suggesting that weather has no effect on these domain-specific measures. The three instances of weather variables that are significant at the 5% confidence level occur for three different weather variables. Temperature is significant at the 5% level in model 18, which considers satisfaction with one's financial situation, whereas solar exposure is significant in model 19 and wind speed at the time of the survey is significant in model 24. On the whole, Table 9 presents strong evidence that weather has practically no effect on responses to domain-specific subjective wellbeing measures like these.

3.2.2. Panel conditioning and weather bias

Differences in weather bias in the HILDA Survey's domain-free and domain-specific variables

Table 9. Weather's effect on domain-specific measures of wellbeing†

	Results for the following models:								
	16	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*
Satisfaction with	Job overall	Employment opportunities	Financial situation	The home in which you live	Local community	Neighbourhood in which you live	Safety	Your health	Amount of free time
Weather—day of interview									
Solar exposure	0.00246	0.00212	0.000877	0.00265‡	0.0000667	−0.000150	0.00157	0.000923	−0.00259
Precipitation	−0.000810	−0.000835	0.000279	−0.00113	−0.000781	−0.00193§	0.000290	0.000701	0.00154
Wind speed (daily mean)	−0.000178	−0.00106	0.00672	0.000670	−0.000554	−0.00806§	0.00538	0.00273	−0.00257
Weather—time of interview									
Mean sea level pressure	−0.000887	−0.00268§	−0.000825	−0.00158	−0.000166	−0.000195	0.000739	−0.000943	0.000686
Temperature	0.000247	−0.00241	−0.00429‡	−0.00336§	0.00402§	0.00101	0.000138	0.00248	0.00205
Relative humidity	0.000461	0.000374	−0.000494	−0.000578	0.000554	0.0000262	0.000409	0.000399	−0.000673
Wind speed	−0.00293	−0.000941	−0.00416	0.00106	0.00113	0.00543	−0.00348	0.000495	0.00958‡
Wind direction (north)	0.0100	−0.000273	0.00111	−0.0153	−0.0132	0.00135	0.0178	−0.00866	0.00978
Wind direction (east)	−0.00274	0.000128	0.0216	−0.0121	−0.00885	0.0253	0.0214	−0.00339	0.0268
Wind direction (west)	0.00464	0.00490	−0.0101	−0.00135	0.000984	0.00527	0.0221	−0.0192	0.0164
Other variables of interest									
Hour	−0.00268	0.00118	0.000150	0.00107	−0.00769§§	−0.00603§§	−0.00703§§	−0.00133	−0.0208§§
Weekend	0.00386	0.0218	0.0136	0.00103	0.0132	−0.0143	0.00248	0.0226§	−0.134§§
Other present	−0.0658§§	−0.0625§§	−0.0422§§	−0.00221	−0.0368‡	−0.0365§§	0.0332§§	−0.0317‡	0.0237
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Postcode fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.531	0.653	0.651	0.564	0.607	0.585	0.583	0.702	0.598
F-statistic (weather)	0.48	0.56	1.05	1.48	0.59	1.26	0.8	0.85	1.36
F-statistic p-value	0.9067	0.8477	0.4013	0.1392	0.8234	0.2492	0.6333	0.5806	0.1906
N	61483	75687	96470	96461	96441	96461	96479	96497	96455

†Individual clustered standard errors of the mean are in parentheses. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed variable descriptions.
‡Significant at the 0.05 level.
§Significant at the 0.1 level.
§§Significant at the 0.01 level.

may arise for reasons other than differences in cognitive complexity. One likely alternative candidate is the order of the questions. For example, Schwarz and Clore (1983) found that priming to attribute mood to the weather removes this influence on self-reported life satisfaction.

As a check of robustness, our second approach uses variation in the complexity of the same life satisfaction question arising from experience. Stating life satisfaction for the first time requires the respondent to translate their internal scale into the scale that is offered in the interview and this challenge can cause the level and accuracy of responses to a given life satisfaction question to change with experience. Toepoel *et al.* (2009), Das *et al.* (2011) and van Landeghem (2012) found evidence of experience effects in European panel studies, including declining self-reported life satisfaction.

Wooden and Li (2014) found that male self-reported life satisfaction and its dispersion decline with the number of times interviewed as part of the HILDA Survey. We focus on males because no time trend exists for women, although the female dispersion of responses does decline significantly. Using this source of exogenous variation in complexity of question for males, we revisit our cognitive complexity hypothesis. Again, we explicitly state the assumption before conducting this test.

Assumption 2. For men, the cognitive complexity of reporting the HILDA Survey measure of life satisfaction declines with experience.

Table 10 presents the results of estimating equation (1) with the inclusion of interaction terms for each weather variable multiplied by the number of times that the respondent has completed the HILDA Survey. Model 25 considers the whole sample and model 26 considers only males.

In the sample with only males we find evidence that weather bias declines with experience. As in model 8, air pressure and solar exposure significantly influence male self-reported life satisfaction. This flexible specification identifies temperature bias in the early panel waves, which is not present in model 1.

More interesting are the experience interaction terms. All 10 weather variable coefficients—of which those on pressure and temperature are significant at the 5% level—have signs indicating that weather bias declines with panel experience. This is strong evidence of the cognitive complexity hypothesis. An important corollary, especially for those studying self-reported life satisfaction with panel data, is that weather bias declines with successive survey waves.

Support for the cognitive complexity hypothesis for the entire sample is less pronounced. This is expected as females do not exhibit the pronounced experience effect that males do in the HILDA Survey. We cannot conclude that any coefficients on the interaction terms are significantly different from 0 at the 5% level, but we see the same striking pattern with the signs on all interaction terms, implying that weather bias declines with panel experience.

3.3. Climate effects

Studies such as Frijters and Van Praag (1998), Rehdanz and Maddison (2005), Brereton *et al.* (2008) and Maddison and Rehdanz (2011) found significant effects of climate on self-reported life satisfaction. These results should not, however, be interpreted as a direct effect of climate on peoples' feelings of wellbeing. First, it is difficult to know whether changes in climate directly enhance self-reported life satisfaction or whether people reporting higher levels of life satisfaction live in certain climates. Second, several indirect mechanisms may be responsible. For example, Rehdanz and Maddison (2005), page 111, hypothesized that climate's influence on self-reported life satisfaction may arise through effects on 'heating and cooling requirements, health, clothing and nutritional needs and recreational activities'.

In this section we use our panel data to show that climate does not appear to provide amenity

Table 10. Examining the effect of survey experience on weather bias†

	Model 25 coefficient	*t-statistic*	*Model 26 coefficient*	*t-statistic*
Weather—day of interview				
Solar exposure	0.00312‡	(1.74)	0.00534§	(2.11)
Precipitation	0.0000929	(0.05)	−0.00117	(−0.43)
Wind speed (daily mean)	−0.00957	(−1.22)	−0.0137	(−1.20)
Weather—time of interview				
Mean sea level pressure	−0.00392§	(−2.43)	−0.00762§§	(−3.25)
Temperature	−0.00519§	(−1.99)	−0.00799§	(−2.16)
Relative humidity	−0.000942	(−1.60)	−0.000986	(−1.17)
Wind speed	0.00656	(1.17)	0.0120	(1.47)
Wind direction (north)	0.0149	(0.52)	−0.00392	(−0.09)
Wind direction (east)	0.0481‡	(1.76)	0.0523	(1.33)
Wind direction (west)	0.0170	(0.64)	−0.0371	(−0.96)
Experience∗solar exposure	−0.000289	(−0.81)	−0.000566	(−1.09)
Experience∗precipitation	−0.00000551	(−0.02)	0.000182	(0.35)
Experience∗wind speed (daily mean)	0.000540	(0.38)	0.00292	(1.46)
Experience∗mean sea level pressure	0.000355	(1.23)	0.00105§	(2.50)
Experience∗temperature	0.000802‡	(1.79)	0.00145§	(2.25)
Experience∗relative humidity	0.000145	(1.40)	0.0000977	(0.66)
Experience∗wind speed	−0.000698	(−0.69)	−0.00211	(−1.45)
Experience∗wind direction (north)	0.00101	(0.19)	0.00474	(0.62)
Experience∗wind direction (east)	−0.00279	(−0.56)	−0.00306	(−0.42)
Experience∗wind direction (west)	−0.00198	(−0.40)	0.00699	(0.99)
Other variables of interest				
Other present	0.0398§§	(3.68)	0.0375§	(2.47)
Hour	−0.00494§§	(−3.07)	−0.00542§	(−2.33)
Weekend	−0.00321	(−0.28)	−0.00662	(−0.40)
Month fixed effects	Yes		Yes	
Wave fixed effects	Yes		Yes	
Postcode fixed effects	Yes		Yes	
Individual fixed effects	Yes		Yes	
R^2 (within)	0.622		0.646	
F-statistic (weather)	4.59		1.62	
F-statistic p-value	0.0463		0.0402	
N	96472		45598	

†Dependent variable, life satisfaction: individual clustered standard errors of the mean are in parentheses. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed variable descriptions.
‡Significant at the 0.1 level.
§Significant at the 0.05 level.
§§Significant at the 0.01 level.

value (as measured by self-reported life satisfaction). Table 11 presents four models, all of which include climate variables. Fixed effects in each model are described at the bottom of Table 11. Note that to identify climate effects we use state rather than postcode fixed effects—within postcodes there is not sufficient climate variation to identify its effects, yet within states, two of which span roughly 20° of latitude, there is considerable climate variability. Also, when individual fixed effects are included in the specification, any climate effect is identified through individuals moving location (and therefore climate) during the nine waves.

Table 11. Examining the effect of climate on life satisfaction†

	Model 27 coefficient	*t-statistic*	*Model 28 coefficient*	*t-statistic*	*Model 29 coefficient*	*t-statistic*	*Model 30 coefficient*	*t-statistic*
Weather—day of interview								
Solar exposure	0.00249‡	(2.42)	0.00310§	(3.04)	0.00213‡	(2.37)	0.00207‡	(2.30)
Precipitation	0.000440	(0.46)	0.000487	(0.50)	0.000337	(0.40)	0.000311	(0.37)
Wind speed (daily mean)	−0.0103‡	(−2.46)	−0.0107‡	(−2.56)	−0.00620§§	(−1.66)	−0.00626§§	(−1.68)
Weather—time of interview								
Mean sea level pressure	−0.00348§	(−4.06)	−0.00342§	(−4.08)	−0.00184‡	(−2.47)	−0.00188‡	(−2.52)
Temperature	−0.00258	(−1.59)	−0.00352‡	(−2.20)	−0.000748	(−0.53)	−0.000775	(−0.55)
Relative humidity	0.000340	(0.92)	0.000527	(1.44)	−0.000186	(−0.59)	−0.000192	(−0.61)
Wind speed	0.00386	(1.29)	0.00434	(1.45)	0.00276	(1.06)	0.00264	(1.01)
Wind direction (north)	0.0424§	(2.77)	0.0349‡	(2.31)	0.0207	(1.55)	0.0200	(1.50)
Wind direction (east)	0.0360‡	(2.54)	0.0259§§	(1.85)	0.0365§	(2.92)	0.0354§	(2.84)
Wind direction (west)	0.0167	(1.22)	0.0189	(1.38)	0.0115	(0.95)	0.0121	(1.01)
Climate variables								
Annual average maximum temperature	−0.00714§§	(−1.72)	−0.00700	(−1.03)	−0.0107	(−1.46)	−0.00856	(−0.80)
Annual average wind speed	0.0335§	(3.17)	0.0420§	(3.75)	0.000122	(0.01)	0.00297	(0.16)
Annual average daily solar exposure	0.0138‡	(2.57)	0.0186§	(3.13)	0.00658	(0.67)	0.00386	(0.38)
Annual rainfall	0.0000372	(1.21)	−0.0000220	(−0.59)	0.0000314	(0.51)	0.00000757	(0.11)
Other variables of interest								
Other present	0.0878§	(6.71)	0.0870§	(6.64)	0.0430§	(4.01)	0.0437§	(4.08)
Hour	−0.00730§	(−3.84)	−0.00774§	(−4.08)	−0.00478§	(−3.00)	−0.00476§	(−2.99)
Weekend	−0.0459§	(−3.54)	−0.0445§	(−3.43)	−0.00662	(−0.59)	−0.00663	(−0.59)
Month fixed effects	Yes		Yes		Yes		Yes	
Wave fixed effects	Yes		Yes		Yes		Yes	
State fixed effects	No		Yes		No		Yes	
Individual fixed effects	No		No		Yes		Yes	

(continued)

Table 11 (*continued*)

	Model 27 coefficient	*t-statistic*	*Model 28 coefficient*	*t-statistic*	*Model 29 coefficient*	*t-statistic*	*Model 30 coefficient*	*t-statistic*
R^2 (within)	0.0949		0.0955		0.610		0.610	
F-statistic (weather)	3.60		3.73		2.53		2.46	
F-statistic (weather) p-value	0.0000		0.0000		0.0047		0.0061	
F-statistic (climate)	6.97		9.19		0.68		0.25	
F-statistic (climate) p-value	0.0000		0.0000		0.6089		0.9112	
N	96472		96472		96472		96472	

†Individual clustered standard errors of the mean are in parentheses. The dependent variable is life satisfaction from waves 1–9 of the HILDA Survey. In addition to those regressors listed in the left-hand column, all models include controls for age and its square, number of household dependents aged between 0 and 24 years and the natural logarithm of nominal household disposable income for the previous financial year in Australian dollars. Dummy variables are also included for disability status, employment status, marital status and education. See Tables 2 and 3 for detailed variable descriptions.
‡Significant at the 0.05 level.
§Significant at the 0.01 level.
§§Significant at the 0.1 level.

Pairwise comparison of models 27 and 28 or models 29 and 30 shows that the inclusion of state dummies does not make much difference to estimated climate coefficients. However, the inclusion of individual fixed effects when estimating coefficients on the climate variables matters greatly. In the absence of individual fixed effects we find significant effects on both wind speed and average daily solar exposure. For example, in model 28, a 1-standard-deviation (2.02 MJ m^{-2}) increase in the annual average of average daily solar exposure yields a 0.038-unit increase in self-reported life satisfaction. F-statistics for the climate variables indicate strong joint significance.

However, we find no climate effects—either individually or jointly—when we use only the variation within individuals to identify them. This result, together with the other cross-sectional studies finding climate effects, suggests that, rather than climate providing amenity value and actually making people more satisfied, certain climates attract, or are already home to, more satisfied people. For example, higher self-reported life satisfaction on the Mediterranean Sea or the US–Mexican border may arise because of the types of people in these places rather than the climate.

4. Conclusion

This paper introduced panel data and highly detailed weather observations to the literature evaluating weather's effect on subjective wellbeing. We detect significant positive effects of global daily solar exposure and significant negative effects of daily mean wind speed and sea level air pressure at the time of the interview on self-reported life satisfaction, though the magnitude of these effects may be judged small. Despite this significance, we find little effect of the omission of weather variables for the estimated coefficients on non-weather variables.

We investigated a leading hypothesis on the cause of this weather effect, namely that the cognitive demands of assessing overall life satisfaction lead respondents to apply heuristics that are based on contemporaneous transient factors. Supporting this hypothesis, we find no influence of weather variables on cognitively simpler domain-specific measures of subjective wellbeing and we find that weather bias declines as individuals become more experienced with the life satisfaction question.

We have also provided evidence—complementary to Graham (2009) and Deaton (2012)—that individual self-reported life satisfaction is more resilient to longer-term changes. Panel data enable us to narrow the potential causes of the documented relationship between climate and self-reported life satisfaction substantially. Our results suggest that the effect of climate on self-reported life satisfaction is close to 0. Instead, we hypothesize that there is geographic clustering of individuals with higher self-reported life satisfaction in locations with higher wind speed and higher solar exposure. This finding suggests that the direct effect of anthropogenic climate change on self-reported life satisfaction is likely to be very small.

Our finding that individual fixed effects matter for estimating weather and climate effects suggests two interesting avenues for future research. First, although Australia is in many ways the ideal country for estimating weather effects, the extent to which our results can be generalized to other countries remains an open question. In particular, no paper in the literature on weather and self-reported life satisfaction considers reports of life satisfaction in developing countries, where respondents may be more exposed to the weather conditions and agriculture plays a larger economic role. Second, this and past studies have tended to focus on one common single-item measure of self-reported life satisfaction. We hypothesize that weather influences less cognitively demanding measures of self-reported life satisfaction less. For example, future research should test the robustness of these results to the use of a multi-dimensional wellbeing measure.

There are many practical implications of our research. First, in many important contexts, such as evaluating the effect of air pollution on self-reported life satisfaction, it is important to control for the weather. Not doing so omits an important factor that is correlated with the variable of interest. Second, steps should be taken in the design of subjective wellbeing surveys to minimize weather bias. This could be achieved by spacing surveys out over time within a given location. Third, because the severity of weather bias declines in longer panels, recently commissioned cross-sectional life satisfaction surveys such as the Gallup World Poll and the UK Office for National Statistics Integrated Household Survey may benefit substantially from supplementary panel surveys that are capable of addressing weather bias.

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Supporting information

Additional 'supporting information' may be found in the on-line version of this article:

'Subjective well-being: why weather matters: Supplementary Tables'.