Subjective Well-Being: Why Weather Matters

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Abstract

We investigate the impact of short-term weather and long-term climate on self-reported life satisfaction using panel data for the first time. We find robust evidence that day-to-day weather variation impacts life satisfaction by a similar magnitude to acquiring a mild disability. Utilising two sources of variation in the cognitive complexity of satisfaction questions, we present evidence that weather bias arises because of the cognitive challenge of reporting life satisfaction. Consistent with past studies, we detect a relationship between long-term climate and life satisfaction without individual fixed effects. This relationship is not robust to individual fixed effects, suggesting climate does not directly influence life satisfaction.

Key words: climate, HILDA Survey, life satisfaction, mood, subjective well-being, weather

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1 Introduction

Social scientists increasingly turn to measures of subjective well-being (SWB) in addition to traditional 'objective' measures of welfare such as GDP, crime levels and health statistics. Recent analysis uses SWB 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).

A key reason that social scientists feel more confident using SWB measures is that several major causes of skepticism toward them have been addressed. Two of the most critical challenges are ensuring the *validity* and the *consistency* of SWB measures. Put simply: *do SWB measures reflect actual well-being, and do they reflect it consistently through time?*

There is a large and growing body of evidence supporting the validity of SWB as a measure. Several studies show a strong association between SWB and objective measures that could conceivably proxy for well-being (i.e., 'convergent validity' studies). Kahneman and Krueger (2006) find a positive correlation between self-appraisal of SWB and appraisal by both friends and strangers; Oswald and Wu (2010) find that amenities with higher hedonic value increase life satisfaction; and Konow and Earley (2008) report correlations between SWB and the duration of genuine 'duchene' smiles, heart rate and blood pressure.

Another literature has identified associations between SWB and measures one might think it should be related to (i.e., 'construct validity' studies). SWB is a useful predictor of suicide, sociability, extroversion and quality of sleep (Boarini et al., 2012). A large literature also documents the sensitivity of SWB to changes in circumstances, such as losing a job or becoming disabled, which are objectively positive or negative (Frijters et al., 2004). SWB measures are also fairly consistent through time. When asked the same SWB question twice on the same day, Krueger and Schkade (2008) find a correlation ranging from 0.6 to 0.7 between a person's answers. Schimmack et al. (2002) show that people tend to reflect on the same information to make SWB judgments at different times, which may explain this consistency.

While this recent work may be enough to placate a skeptic, the validity and consistency of SWB measures is not perfect, as they reflect a variety of factors that are of little empirical interest. SWB measures may be sensitive to question order (Strack et al., 1988; Kahneman and Deaton, 2010) and the way the survey is introduced (Ubel et al., 2001). Recent pleasant experiences, such as finding a dime on a photocopier immediately prior to the survey (Schwarz, 1987) or receiving a chocolate bar (Münkel et al., 1987), increase SWB by magnitudes that cannot be explained by the income effect. Similarly, Schwarz et al. (1987) report a significant increase in life satisfaction when respondents are in a more comfortable room.

Campbell (1981, p. 23) argues that for reports of SWB to be accurate, people must be able to 'describe [well-being] with candor and accuracy.' Diener et al. (2009) agree, suggesting (p. 19): 'the only link that creates potential problems for the measurement of well-being is between the evaluation itself and a person's judgment of the evaluation'. In this paper we investigate Campbell's condition, considering the influence of contemporaneous transient weather on SWB in a large nationally representative Australian panel survey. We follow convention and refer to weather as a short-term phenomenon and climate as a long-term phenomenon, and we operationalise these definitions in our data by using meteorologic observations for a particular location, at a particular hour or on a particular day to measure the weather. Climate is calculated as an annual average over the decade from January 1, 2000 to December 31, 2009.

In many cases a disconnect between well-being and a person's judgment of well-being is of theoretical interest but of practical irrelevance. For example, judgment biases may be so small, and their causes sufficiently random, that in large representative samples they are of no practical consequence (Boarini et al., 2012). In addition, for non-transient factors like question order, once the bias is identified it may be nullified by appropriate study design. This solution relies on potential sources of bias being identified in the first place.

Weather bias – which arises when transient weather influences long-run measures of SWB such as life satisfaction – may not be avoided in large samples and is difficult to overcome through study design. The first main challenge arises because weather may drive underlying variables of interest. One prominent example is the way wind speed and direction causes variation in local air pollution levels (Levinson, 2012). If wind affects SWB then estimates of the influence of pollution on SWB may be biased. Second, within a given location, weather is highly temporally correlated and could influence inference based on time-variation in treatment. Studies of the impact of, for example, sporting events, natural disasters or terrorist attacks should mitigate the risk that variation in weather before and after the event influences inference. A better understanding of the influence of weather on SWB is therefore of practical, as well as purely theoretical, interest.

In this study, we evaluate the theoretical and practical relevance of weather on self-reported life satisfaction. This study is not the first to consider this question. Schwarz and Clore (1983) analysed a sample of 84 respondents to a telephone survey and is the most widely cited study on this topic. Considering the effects of 'sunny' and 'rainy' days, the authors detect large and significant impacts on self-reported life satisfaction with subjects not primed to attribute their mood to the weather. On a scale from one to ten, respondents on a sunny day reported mean life satisfaction of 6.57, and those surveyed on a rainy day reported 4.86. The authors speculate that weather affects mood, which is one of several transient factors respondents reflect on in expressing their own life satisfaction.

Weather effects of the magnitude of Schwarz and Clore (1983) have, to the best of our knowledge, never been replicated. Recent studies use large cross-sectional data sets and provide conflicting punch lines. Connolly (2013) finds a significant negative effect of more precipitation and higher temperature, while Levinson (2012) finds no effect of precipitation and a positive (though declining) effect of temperature on life satisfaction. Barrington-Leigh (2008) reports that life satisfaction varies significantly with the amount of recent cloud cover. Finally, Lucas and Lawless (2013) find little evidence of a relationship between any of a large number of weather variables and life satisfaction.

Despite uncertainty over the relationship between life satisfaction and weather, there is evidence that weather influences mood (Watson, 2000; Denissen et al., 2008) and risk-taking behavior (Simonsohn, 2010). It has even been found that morning sunshine in the city of a country's leading stock exchange is strongly correlated with stockmarket returns (Hirshleifer and Shumway, 2003).

Our estimated weather effects are novel for four reasons. First, and most importantly, ours is the first paper to include individual fixed effects while estimating the effect of weather on 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 life satisfaction has substantial potential to create omitted variable bias in estimates of the effect of weather on life satisfaction.

Second, Barrington-Leigh (2008), Connolly (2013), Levinson (2012) and Lucas and Lawless (2013) use weather variables for the day of, rather than at the precise time of, collection of life satisfaction data. Using a time marker for the start of the survey in which life satisfaction data are collected, we are able to use weather data at almost precisely the time of interview. Previous studies that find 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) consider precipitation and temperature variables and Barrington-Leigh (2008) includes 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 behavior (Frijters and Van Praag, 1998; Keller et al., 2005; Denissen et al., 2008). These six weather variables are described by biometeorologists San-Gil, González de Rivera, and González (1991, p. 402) as providing ‘the complete weather picture’.

Because weather variables tend to be correlated, considering all weather variables together is important when evaluating which ones actually matter. For example, because cloud cover and temperature are negatively correlated, Barrington-Leigh’s (2008) combination of significant cloud cover and insignificant temperature may actually reconcile with Levinson’s (2012) significant temperature effects in the absence of a control for cloud cover.

Fourth, our weather data are very spatially detailed, removing another potential source of noise in the regressors when compared to previous studies. Almost all weather variables are collected from within 20km of the survey location. The mean distance from the location of collection of life satisfaction data to the nearest weather station is 8.9 kilometres (km). The values for the 10th, 50th and 90th percentiles of this distance are 2.45km, 6.76km and 17.26km respectively.

With these enhancements, the first main finding of the paper is the significant weather effects we estimate. Using ordinary least squares (OLS) 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 life satisfaction.

The second main contribution of the paper is evidence supporting the hypothesis that the cognitive complexity of reporting 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 well-being, which we assume are cognitively simpler to report than the ‘domain-free’ life satisfaction measure (Strack et al., 1991). We find almost no significant weather effects for all of these variables, suggesting that less cognitively complex questions suffer less from weather bias.

Second, based on evidence of ‘panel conditioning’ in the 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 third main contribution comes from revisiting past studies of the effect of climate on life satisfaction while using panel data and individual fixed effects. Similar to past studies, without individual fixed effects we find significant effects of climate on life satisfaction (Frijters and Van Praag, 1998; Rehdanz and Maddison, 2005; Brereton et al., 2008; Ambrey and Fleming, 2011; Maddison and Rehdanz, 2011). Once we allow for individual fixed effects, therefore estimating the climate effect using only within-person climate variation arising when people move their household location, we find no effect of climate on life satisfaction. This suggests that causation does not flow directly from climate to life satisfaction; rather that previously omitted time-invariant individual characteristics influence both location and life satisfaction. This new puzzle – that weather matters but climate doesn't – is consistent with the finding of Graham (2009) and Deaton (2012) that people's capacity to adapt to permanent changes tends to mediate well-being effects, while changes people cannot adapt to – such as uncertain weather – have a much stronger effect.

The remainder of the paper proceeds as follows. Section 2 describes the econometric framework 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 SWB, a proxy for actual well-being. Adopting a reduced-form specification, we estimate the following linear regression model:

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

Prior to 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 post code), 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 life satisfaction (Argyle 1999; Diener and Lucas 1999) the scope for omitted variable bias in their absence is large. Indeed, with our life satisfaction data the R-squared of an OLS regression fitting only individual-specific dummy variables as independent variables is 0.6.

As one example of a source of omitted variable bias consider 'active' people, who tend to be both more satisfied than average and busier than average when the sun is shining, and therefore tend not to be available to answer the HILDA Survey in sunny conditions. These satisfied active people are likely to be overrepresented in cloudy and rainy 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, in order 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 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 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 ten 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, in order to estimate climate effects, we include climate variables in our specification and remove post code fixed effects.

We also include individual time-specific controls, X_{it}. These are age and its square, the number of household dependents aged between 0 and 24, and the natural log 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 life satisfaction (Frijters et al., 2004).

Finally, we investigate three other non-weather sources of potential bias. Based on Csikszentmihalyi and Hunter (2003) we include a dummy variable indicating if the interview was conducted on a weekend and a variable measuring the hour of day at which the interview is 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 related to the time of day, such as tiredness. Finally, following Wooden et al. (2009), we include an indicator variable which is equal to one if another person is present during the interview.

2.2. Data

Two sources are used in the construction of the data set. All non-weather variables are obtained from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, while weather variables are extracted from the Australian Bureau of Meteorology (BoM) database.

2.2.1. Household, Income and Labour Dynamics in Australia (HILDA) Survey

The well-being data used in this study are drawn from waves one to nine 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 (BHPS) and the German Socio-Economic Panel (GSOEP).

The survey commenced in 2001 with a national probability sample of Australian households. Personal interviews were completed at 7,682 households in wave one 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 pursued in the subsequent waves of interviews, which are conducted approximately one year apart. Interviews are conducted with all adults (defined as persons aged 15 years or older on 30 June 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 re-interview rates (the proportion of respondents from one wave who are successfully interviewed the next) are reasonably high, rising from 87 per cent in wave two to 96.3 per cent in wave nine.

The main outcome variable used in this analysis is a measure of overall life satisfaction. It is constructed from responses to a single item scored on an eleven-point scale ranging from zero to ten. Single-item life satisfaction questions are the most commonly used measure of SWB by economists (Dolan et al., 2008). The question, delivered by interviewer, either in person or by telephone is: 'All things considered, how satisfied are you with you life?' A score of zero is labelled and described as 'totally dissatisfied' and a score of ten labelled and described as 'totally satisfied'. This question is almost identical to a question included every year in the GSOEP 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 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 zero to ten. Finally, the HILDA Survey also provides the controls for age, number of household dependents, the natural log of nominal household equivalised 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 zero so we add one to each value before taking the log. 440 observations report negative real household equivalised disposable income and these are dropped from the sample.

For our purposes, one advantage of using data from the HILDA Survey, rather than the BHPS and GSOEP, is the spread of weather conditions in Australia. We are able to consider weather and climate effects in many highly heterogeneous locations. Because interviews are conducted between August and February, we are also able to consider weather effects in different seasons. It seems plausible that 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 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 Australian Bureau of Meteorology (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 life satisfaction in a model that 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 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 degrees in latitude and longitude (roughly $5km^2$). 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 recorded at the time of the interview. There are four interview time-specific weather variables – mean sea level pressure, temperature, wind speed and relative humidity – which are recorded at three-hour intervals throughout the day (BoM provides weather variables at 3am, 6am, ... 9pm and 12am). Global solar exposure and precipitation are recorded on a daily basis 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 time of interview.

As a robustness check, and to consider the effects of season and climate on 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 approximately 850 weather stations in operation from January 2001 until the completion of wave nine in 2010. Figure 1 plots the location of all stations operating at the end of HILDA Survey wave nine, with longitude on the x-axis and latitude on the y-axis. Over 90 percent of observations are within 20km of the closest weather station.

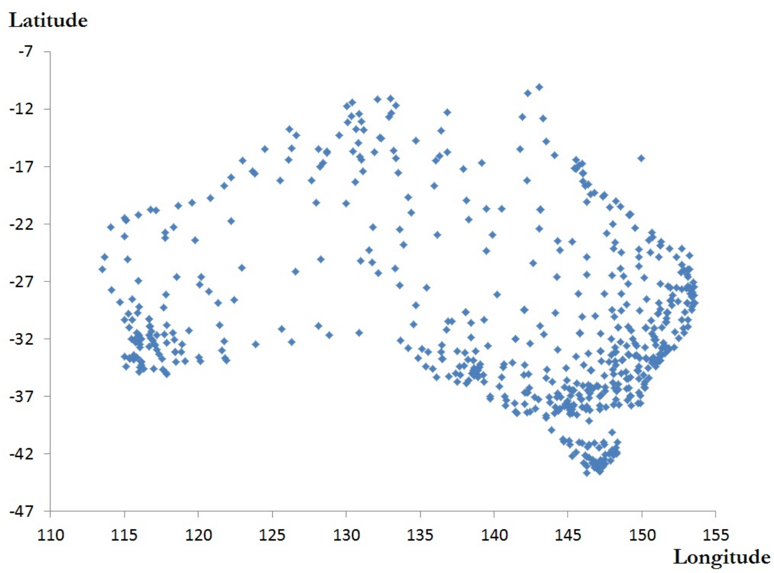

Figure 1: Map of weather stations

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 spread across roughly 9,000 CDs, each weather station may map to several CDs. Australia has approximately 37,000 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 in order to better measure the weather at a particular location.

3 Results

3.1. Weather effects

3.1.1. Main results

Table 5 presents results from our baseline attempts at estimating weather effects. Model 1 incorporates month and wave fixed effects only, while Model 2 also includes location fixed effects. These specifications are included to replicate the approach in a recent analysis by Connolly (2013) and they help illustrate the importance of adopting individual and post code fixed effects (as in Model 4). Like Connolly (2013), Models 1 and 2 detect a significant effect of temperature on life satisfaction; warmer weather reduces life satisfaction. We also find that higher sea level air pressure causes disutility and that the direction of the wind matters.

Time-invariant post code 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 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 life satisfaction, even if transient weather has no impact on life satisfaction. In Model 3 we include post code level fixed effects to address this empirical challenge and find that coefficients on solar exposure, temperature and humidity are no longer significant.

Model 4, which is our preferred specification, also controls for time-invariant individual specific heterogeneity. The increase in the R-squared 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 life satisfaction and this suggests that the scope for omitted variable bias is significantly reduced in Model 4.

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 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 life satisfaction measures, but that the strength and direction of the effect depends on local factors. Neither temperature nor precipitation coefficients are significant in Model 4, suggesting that our new variables, solar exposure and sea level pressure, are more important than those traditionally used to evaluate the impact of weather on life satisfaction. An F-statistic for the joint significance of the weather variables is reported in all tables in this paper and for Models 1 to 4 the hypothesis that weather has no influence on self-reported life satisfaction is strongly rejected.

Considering the size of the effects in Model 4, if total daily solar exposure is one standard deviation (6.43 MJ/m^2) above average, we estimate that life satisfaction is 0.012 points higher. A one standard deviation decrease in mean sea level pressure (7.08 hPa) increases life satisfaction in our model by 0.016 and a one standard deviation decrease in wind speed (1.91 m/s) increases life satisfaction by 0.014.

How large are these effects? It is informative to compare these effects to non-weather coefficients in Model 4. These are presented in Model 6 from Table 6. To place these magnitudes into context, first note that there is a substantial component of SWB 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 life satisfaction by even one 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 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 ten percent increase in household nominal equivalised income is associated with an increase in life satisfaction of 0.0024, meaning that day-to-day weather variation has an effect of roughly similar magnitude to doubling income.

Three other coefficients are of note as potential sources of bias. Life satisfaction declines throughout the day, a ten hour difference in interview time resulting in a roughly 0.05 unit decrease in life satisfaction. The coefficient on the variable indicating whether another person was present during the interview increases life satisfaction by approximately 0.04 units. Finally, as in Csikszentmihalyi and Hunter (2003) and Kahneman and Deaton (2010), we initially find evidence (in Models 1, 2 and 3) that interviews on the weekend influence life satisfaction; however, the effect disappears with individual fixed effects.

The existence of significant coefficients is likely to be of theoretical interest; however, the practical importance of the bias deserves mention. In Table 6, we present three models: Model 5 contains only weather variables; Model 6 is identical to Model 4 in Table 5 and is presented with coefficients on the full set of controls; and Model 7 omits all weather variables. 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 are included in the regression; however this is unusual and coefficients mostly change by less than ten percent.

Comparing Models 5 and 6, the significant coefficients are somewhat different (especially the coefficient on relative humidity), highlighting the importance of controlling for individual-specific influences on life satisfaction when estimating the effect of weather on life satisfaction.

The omission of weather does not appear to substantially influence non-weather variables in this study. However, given the rapidly expanding uses of SWB data, situations may arise where weather controls reduce bias substantially. For example, as Levinson (2012) notes, wind speed and air quality are correlated and any study attempting to estimate the effect of air pollution on 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 life satisfaction (Kavetsos and Szymanski, 2010; Metcalfe et al., 2011) should take measures to ensure that changes in the weather prior to and after the event do not drive the observed changes in SWB.

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) finds that females are typically more responsive to weather variables, while Lucas and Lawless (2013) find a small heterogeneous effect depending on the season. The first two columns in Table 7 display results when Model 4 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, and neither 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 one-third and 70 percent that of males and neither is found to be significantly different from zero. Female life satisfaction is more responsive to wind speed than that of males and wind direction appears to play a similarly significant role across genders.

The coefficients on climate and season interactions – which are generated by multiplying the weather variables by their annual and monthly (during the month of the response) averages – are estimated in Models 10-12 of Table 8, and 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: while 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 bliss point.

Table 9 presents results from the inclusion of non-linear effects both through inclusion of squared weather terms and additional dummy variables indicating if weather is ‘extreme’ (below the 5th percentile and above 95th percentile for all observations). In both cases we find no evidence of non-linear effects.

Finally, in Table 10, we consider the effect of lagged weather variables, both three hours and six hours before the survey commences. In Model 15, which does not interact three and six hour lagged weather variables with those at the time of the interview, none of the weather variables are significant. Once we allow for these interactions in Model 15 we find significant coefficients on six-hour lagged wind speed and its interaction with the wind speed at the time of interview. The change in wind speed matters, with high wind speed six hours prior to the interview and low wind speed at the time of interview increasing life satisfaction.

3.1.3. Interpretation

Our results are different to, yet not inconsistent with, the results of Barrington-Leigh (2008), Connolly (2013), Levinson (2012) and Lucas and Lawless (2013). We believe this is mainly a consequence of four novel aspect of our study. First, we use panel data and Table 5 shows that the absence of individual fixed effects yields a significant temperature effect similar to Connolly (2013). Second, by including more variables we are able to detect new relationships. For example, we detect a highly significant coefficient on air pressure, a variable 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) find none.

Coefficients on solar exposure and wind speed in Model 4 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 hypothesised by Schwarz and Clore (1983) to influence life satisfaction. Less obvious is why sunshine matters for males and not females. Without speculating why, we note that gender differences in 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 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 its strongest correlations are with wind speed and temperature. Internet search 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 finds 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 three and six hours prior to interview in Table 10 and found no significant effects. We refrain from speculating further on the causes, noting that it is among the most robust weather influences we find and that its mechanism deserves further empirical attention.

Finally, we put forward three potential explanations for the hour of day effect. First, those interviewed later in the day may be working longer hours (surveys are rarely conducted at the workplace) and we do not control for this in our specification. Second, those answering the question later in the day may exhibit ‘grumpiness’ at having to fill out a survey in the evening. Third, responses later in the day may reflect tiredness, which may be associated with a decrease in perceived life satisfaction.

3.2. Cognitive complexity and weather bias

3.2.1. Domain-specific satisfaction

Strack et al. (1991) are 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 note (at p. 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) demonstrate an effect of the German national football team's performance on 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 well-being. First, we make explicit the assumption required to conduct this test:

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

Table 11 presents the results of estimating Model 4 with 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 life satisfaction, we find that in all nine domain-specific models the weather variables are never jointly significant, even at the ten percent level. Of the 90 weather coefficients estimated, three are significant at the 5 percent level and eight are significant at the ten percent level. This is slightly less significance than one would expect randomly, further suggesting that weather has no impact on these domain-specific measures. The three instances of weather variables significant at the 5 percent confidence level occur for three different weather variables. Temperature is significant at the 5 percent level in Model 19, which considers satisfaction with one's financial situation, while solar exposure is significant in Model 20 and wind speed at the time of the survey is significant in Model 25. On the whole, Table 11 presents strong evidence that weather has practically no effect on responses to domain-specific SWB 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 may arise for reasons other than differences in cognitive complexity. One likely alternative candidate is question order. For example, Schwarz and Clore (1983) find that priming to attribute mood to the weather removes this influence on life satisfaction.

As a robustness check, 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 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) find evidence of experience effects in European panel studies, including declining life satisfaction.

Wooden and Li (forthcoming) find that male 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 question complexity for males, we revisit our cognitive complexity hypothesis. Again, we explicitly state the assumption prior to conducting this test:

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

Table 12 presents coefficient estimates from our preferred model (Model 4) with the inclusion of interaction terms for each weather variable multiplied by the number of times the respondent has completed the HILDA survey. Model 26 considers the whole sample and Model 27 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 life satisfaction. This flexible specification identifies temperature bias in the early panel waves, which is not present in Model 4.

More interesting are the experience interaction terms. All ten weather variable coefficients – of which those on pressure and temperature are significant at the 5 percent 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 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 males do in the HILDA survey. We cannot conclude that any coefficients on the interaction terms are significantly different from zero at the five percent level, however, 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) find significant effects of climate on life satisfaction. These results should not, however, be interpreted as a direct effect of climate on peoples' feelings of well-being. First, it is difficult to know whether changes in climate directly enhance life satisfaction or whether more satisfied people live in certain climates. Second, a number of indirect mechanisms may be responsible. For example, Rehdanz and Maddison (2005, p. 111) hypothesise that climate's influence on 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 value (as measured by life satisfaction). Table 13 presents four models, all of which include climate variables. Fixed effects in each model are described at the bottom of the table. Note that in order to identify climate effects we use state rather than post code fixed effects – within post codes there is not sufficient climate variation to identify its effects, yet within states, two of which span roughly 20 degrees of latitude, there is considerable climate variability. Also, when individual fixed effects are included in the specification, any climate effect is identified through by individuals moving location (and therefore climate) during the nine waves.

Pair-wise comparison of Models 28 and 29 or Models 30 and 31 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 a great deal. In the absence of individual fixed effects we find significant effects on both wind speed and average daily solar exposure. For example, in model 29, a one standard deviation (2.02 MJ/m^2) increase in the annual average of average daily solar exposure yields a 0.038 unit increase in 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 life satisfaction on the Mediterranean Sea or the U.S.-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 well-being. 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 life satisfaction.

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 SWB 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 life satisfaction is more resilient to longer-term changes. Panel data enables us to substantially narrow the potential causes of the documented relationship between climate and life satisfaction. Our results suggest that the impact of climate on life satisfaction is close to zero. Instead, we hypothesise that there is geographic clustering of individuals with higher life satisfaction in locations with higher wind speed and higher solar exposure. This finding suggests that the direct impact of anthropogenic climate change on 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 generalised to other countries remains an open question. In particular, no paper in the literature on weather and life satisfaction considers 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 life satisfaction. We hypothesise that weather influences less cognitively demanding measures of life satisfaction less. However, this hypothesis is yet to be tested.

There are a number of practical implications of our research. First, in many important contexts, such as evaluating the effect of air pollution on 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 SWB surveys to minimise 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, capable of addressing weather bias.

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Table 1: Summary of variables

Variable	Obs	Mean	Std.Dev	Min	Max	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 equivalised 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
Seperated (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
Grad. Diploma/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
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 (megajoules per square metre). 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 here: http://www.bom.gov.au/climate/austmaps/metadata-daily-solar-exposure.shtml
Precipitation	Precipitation in the 24 hours before 9am (local time) in mm.
Wind speed (daily mean)	Mean daily wind speed in m/s.
Mean sea level pressure	Mean sea level pressure in hectopascals (hPa).
Temperature	Dew point temperature observation in degrees C.
Relative humidity	Relative humidity in percentage.
Wind speed	Wind speed measured in m/s.
Wind direction (north)	Indicator variable equal to one if wind direction is greater than 315 degrees and less than 45 degrees.
Wind direction (east)	Indicator variable equal to one if wind direction is greater than 45 degrees and less than 135 degrees.
Wind direction (west)	Indicator variable equal to one if wind direction is greater than 135 degrees and less than 225 degrees.
Wind direction (south)	Indicator variable equal to one if wind direction is greater than 225 degrees and less than 315 degrees.
Other variables of interest	
Hour	Time of interview rounded to the nearest of 0300h, 0600h, 0900h, 1200h, 1500h, 1800h, 2100h, 2400h.
Weekend	Indicator variable equal to one if interview occurred on Saturday or Sunday.
Other present	Indicator variable equal to one if respondent answered yes to the following questions: Were any other adults present during any of this interview?
Controls - continuous	
Age	Age last birthday at June 30 in the year the survey wave begins.
Household dependents	Number of dependent children aged 0-24.
Household income	Nominal household equivalised income. Calculated as household financial year disposable income divided by 1+(Number of adults 15 years and over-1)*0.5+(Number of dependents under 15 years)*0.3.

Table 3: Variable descriptions (II)

Variable	Description
Controls - indicators	
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 impact 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 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.
De facto	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.
Post graduate	Respondent stated their highest education level achieved as masters or doctorate.
Graduate diploma/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.

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

Table 5: Baseline estimates of weather's impact of life satisfaction

Dependent variable: Life satisfaction	Model 1 Coefficient	t-statistic	Model 2 Coefficient	t-statistic	Model 3 Coefficient	t-statistic	Model 4 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**	0.00000197	(0.01)	(2.46)	-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	Y		Y		Y		Y	
Wave fixed effects	Y		Y		Y		Y	
State fixed effects	N		Y		N		N	
Postcode fixed effects	N		N		Y		Y	
Individual fixed effects	N		N		N		Y	
R-squared	0.0941		0.0944		0.143		0.622	
F-stat (weather)	4.47		4.39		2.51		2.53	
F-stat p-value	0.0000		0.0000		0.0052		0.0048	
N	96472		96472		96472		96472	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 6: Omission of weather variables

Dependent variable: Life satisfaction	Model 5 Coefficient	Model 6 Coefficient	Model 7 Coefficient
Weather - day of interview			
Solar exposure	0.00175*	0.00191**	
Precipitation	0.000382	0.000179	
Wind speed (daily mean)	-0.00813**	-0.00710*	
Weather - time of interview			
Mean sea level pressure	-0.00215***	-0.00223***	
Temperature	-0.00206	-0.00141	
Relative humidity	-0.000570**	-0.000242	
Wind speed	0.00346	0.00339	
Wind direction (north)	0.0203	0.0190	
Wind direction (east)	0.0346***	0.0348***	
Wind direction (west)	0.0107	0.00815	
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***
Seperated		-0.398***	-0.424***
Divorced		-0.146**	-0.158***
Widowed		-0.126	-0.161**
Post graduate		-0.160	-0.132
Graduate diploma/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	Y	Y	Y
Wave fixed effects	Y	Y	Y
State fixed effects	N	N	N
Postcode fixed effects	Y	Y	Y
Individual fixed effects	Y	Y	Y
R-squared	0.617	0.622	0.614
F-stat (weather)	2.75	2.53	
F-stat p-value	0.0022	0.0048	
N	96493	96472	115989

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level.
See Tables 2 and 3 for detailed variable descriptions.

Table 7: Gender

Dependent variable: Life satisfaction	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	Y		Y	
Wave fixed effects	Y		Y	
Postcode fixed effects	Y		Y	
Individual fixed effects	Y		Y	
R-squared	0.646		0.616	
F-stat (weather)	2.11		1.4	
F-stat p-value	0.0203		0.1737	
N	45598		50874	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 8: Weather-season and weather-climate interactions (coefficients $\times$ 100)

Dependent variable: Life satisfaction	Model 10 Coefficient	t-stat.	Model 11 Coefficient	t-stat.	Model 12 Coefficient	t-stat.
Weather - day of interview						
Solar exposure	0.36	(0.81)	-0.104	(-0.15)	-0.0287	(-0.04)
Precipitation	-0.137	(-0.97)	0.214	(0.95)	0.137	(0.59)
Mean daily wind speed	0.255	(0.23)	0.0485	(0.05)	0.262	(0.24)
Weather - time of interview						
Mean sea level pressure	-0.231***	(-3.06)	-0.217***	(-2.89)	-0.223***	(-2.94)
Temperature	0.551	(0.92)	1.06	(1.18)	1.03	(1.11)
Relative humidity	-0.0228	(-0.71)	-0.0224	(-0.70)	-0.0222	(-0.70)
Wind speed	0.33	(1.25)	0.343	(1.30)	0.321	(1.21)
Wind direction (north)	1.79	(1.33)	1.94	(1.44)	1.79	(1.33)
Wind direction (east)	3.43***	(2.71)	3.53***	(2.80)	3.42***	(2.70)
Wind direction (west)	0.803	(0.66)	0.885	(0.73)	0.801	(0.66)
Weather - month interactions						
CD monthly average daily solar exposure	-0.0311	(-0.03)			0.187	(0.17)
CD monthly average daily wind speed	-0.0989	(-0.03)			2.3	(0.47)
CD monthly average daily max temperature	0.0685	(0.06)			-0.0493	(-0.04)
CD average monthly precipitation	0.00167	(0.04)			0.00644	(0.16)
Solar exposure day*month interaction	-0.00777	(-0.36)			-0.0145	(-0.63)
Wind speed day*month interaction	-0.218	(-0.88)			-0.559	(-0.62)
Max temperature day*month interaction	-0.0314	(-1.17)			-0.0194	(-0.47)
Precipitation day*month interaction	0.00196	(1.35)			0.00281*	(1.75)
Weather - year interactions						
CD annual average daily solar exposure			-3.27	(-1.05)	-3.49	(-1.12)
CD annual average daily wind speed			-2.86	(-0.46)	-5.12	(-0.65)
CD annual average daily max temperature			-4.34	(-0.68)	-4.32	(-0.66)
CD annual average monthly precipitation			-0.0298	(-0.99)	-0.0305	(-1.01)
Solar exposure day*year interaction			0.0159	(0.44)	0.0281	(0.73)
Wind speed day*year interaction			-0.195	(-0.76)	0.366	(0.39)
Max temperature day*year interaction			-0.0523	(-1.34)	-0.0316	(-0.51)
Precipitation day*year interaction			-0.0002	(-0.90)	-0.000354	(-1.53)
Other variables of interest						
Hour	-0.498***	(-3.09)	-0.503***	(-3.13)	-0.501***	(-3.11)
Weekend	-0.277	(-0.24)	-0.276	(-0.24)	-0.282	(-0.25)
Other present	3.94***	(3.64)	3.96***	(3.66)	3.95***	(3.65)
Month fixed effects	Y		Y		Y	
Wave fixed effects	Y		Y		Y	
Postcode fixed effects	Y		Y		Y	
Individual fixed effects	Y		Y		Y	
R-squared	0.622		0.622		0.622	
F-stat (weather)	1.8		1.75		1.46	
F-stat p-value	0.0201		0.0254		0.0611	
N	96472		96472		96472	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 9: Non-linearities

Dependent variable: Life satisfaction	Model 13 Coefficient	t-statistic	Model 14 Coefficient	t-statistic
Weather - day of interview				
Solar exposure	0.000338	(0.10)	0.00230**	(2.09)
Precipitation	0.000474	(0.34)	-0.000335	(-0.27)
Wind speed (daily mean)	0.00925	(0.87)	-0.00471	(-1.09)
Weather - time of interview				
Mean sea level pressure	0.0414	(0.35)	-0.00276***	(-2.89)
Temperature	0.000536	(0.11)	-0.00311*	(-1.91)
Relative humidity	-0.000240	(-0.19)	-0.000340	(-0.96)
Wind speed	0.00411	(0.60)	0.00317	(1.04)
Wind direction (north)	0.0203	(1.50)	0.0204	(1.50)
Wind direction (east)	0.0361***	(2.86)	0.0375***	(2.95)
Wind direction (west)	0.00893	(0.73)	0.00824	(0.68)
Weather - non-linearities				
Solar exposure squared	0.0000458	(0.48)		
Precipitation squared	-0.00000475	(-0.20)		
Wind speed (daily mean) squared	-0.00157	(-1.60)		
Mean sea level pressure squared	-0.0000215	(-0.37)		
Temperature squared	-0.0000539	(-0.44)		
Relative humidity squared	-5.68e-08	(-0.01)		
Wind speed squared	-0.0000654	(-0.12)		
Weather - extremes				
Solar exposure low			0.0176	(0.73)
Solar exposure high			0.0157	(0.59)
Precipitation low				
Precipitation high			0.0150	(0.52)
Wind speed (daily mean) low			-0.0230	(-0.87)
Wind speed (daily mean) high			-0.0399	(-1.57)
Mean sea level pressure low			-0.0362	(-1.48)
Mean sea level pressure high			0.00155	(0.07)
Temperature low			-0.0310	(-1.32)
Temperature high			0.0386	(1.45)
Relative humidity low			0.000329	(0.01)
Relative humidity high			0.0327	(1.52)
Wind speed low			0.00772	(0.35)
Wind speed high			0.0204	(0.80)
Other variables of interest				
Hour	-0.00492***	(-3.04)	-0.00513***	(-3.18)
Weekend	-0.00249	(-0.22)	-0.00215	(-0.19)
Other present	0.0397***	(3.66)	0.0395***	(3.65)
Month fixed effects	Y		Y	
Wave fixed effects	Y		Y	
Postcode fixed effects	Y		Y	
Individual fixed effects	Y		Y	
R-squared	0.622		0.622	
F-stat (weather)	1.74		1.69	
F-stat p-value	0.0293		0.0210	
N	96472		96472	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 10: Lagged weather variables

Dependent variable: Life satisfaction	Model 15 Coefficient	t-statistic	Model 16 Coefficient	t-statistic
Weather - day of interview				
Solar exposure	0.00198**	(2.06)	0.00160	(1.60)
Precipitation	0.000114	(0.13)	0.000366	(0.42)
Wind speed (daily mean)	-0.00883*	(-1.73)	-0.00987*	(-1.93)
Weather - time of interview				
Mean sea level pressure	-0.00405	(-1.00)	0.0205	(0.35)
Temperature	-0.000708	(-0.20)	0.000992	(0.23)
Relative humidity	-0.000271	(-0.68)	0.000616	(0.80)
Wind speed	0.00393	(1.36)	0.00851*	(1.95)
Wind direction (north)	0.0177	(1.29)	0.0164	(1.19)
Wind direction (east)	0.0354***	(2.76)	0.0348***	(2.70)
Wind direction (west)	0.00761	(0.62)	0.00794	(0.65)
Mean sea level pressure$_{t-3}$	0.00342	(0.55)	0.0270	(0.46)
Temperature$_{t-3}$	-0.00117	(-0.31)	-0.00334	(-0.53)
Relative humidity$_{t-3}$	-0.0000172	(-0.03)	0.000538	(0.40)
Wind speed$_{t-3}$	-0.00121	(-0.39)	-0.00637	(-1.13)
Mean sea level pressure$_{t-6}$	-0.00174	(-0.48)	-0.000803	(-0.21)
Temperature$_{t-6}$	0.000634	(0.31)	0.00351	(0.58)
Relative humidity$_{t-6}$	0.0000997	(0.15)	0.000645	(0.50)
Wind speed$_{t-6}$	0.00230	(0.74)	0.0149**	(2.44)
MSLP*MSLP$_{t-3}$			-0.0000241	(-0.42)
Temp*Temp$_{t-3}$			0.0000948	(0.36)
RH*RH$_{t-3}$			-0.00000794	(-0.47)
Wind speed*wind speed$_{t-3}$			0.00103	(1.30)
MSLP*MSLP$_{t-6}$				
Temp*Temp$_{t-6}$			-0.000161	(-0.57)
RH*RH$_{t-6}$			-0.00000946	(-0.55)
Wind speed*wind speed$_{t-6}$			-0.00206**	(-2.37)
Other variables of interest				
Other present	0.0395***	(3.64)	0.0396***	(3.65)
Hour	-0.00446**	(-2.01)	-0.00455**	(-1.98)
Weekend	-0.00383	(-0.33)	-0.00350	(-0.30)
Month fixed effects	Y		Y	
Wave fixed effects	Y		Y	
Postcode fixed effects	Y		Y	
Individual fixed effects	Y		Y	
R-squared	0.622		0.622	
F-stat (weather)	1.64		1.34	
F-stat p value	0.0565		0.1231	
N	95894		95894	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 11: Weather's impact on domain-specific measures of wellbeing

Model Satisfaction with:	17 Job overall	18 Employ. opportunities	19 Financial situation	20 The home in which you live	21 Local community	22 Neigh'hood in which you live	23 Safety	24 Your health	25 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	Y	Y	Y	Y	Y	Y	Y	Y	Y
Wave fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Postcode fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.531	0.653	0.651	0.564	0.607	0.585	0.583	0.702	0.598
F-stat (weather)	0.48	0.56	1.05	1.48	0.59	1.26	0.8	0.85	1.36
F-stat 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

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 12: Panel experience and weather bias

Dependent variable: Life satisfaction	Model 26 Coefficient	t-statistic	Model 27 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	Y		Y	
Wave fixed effects	Y		Y	
Postcode fixed effects	Y		Y	
Individual fixed effects	Y		Y	
R-squared	0.622		0.646	
F-stat (weather)	4.59		1.62	
F-stat p value	0.0463		0.0402	
N	96472		45598	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

Table 13: Climate and life satisfaction

Dependent variable: Life satisfaction	Model 28 Coefficient	t-statistic	Model 29 Coefficient	t-statistic	Model 30 Coefficient	t-statistic	Model 31 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 ave. max tempertature	-0.00714*	(-1.72)	-0.00700	(-1.03)	-0.0107	(-1.46)	-0.00856	(-0.80)
Annual ave. wind speed	0.0335***	(3.17)	0.0420***	(3.75)	0.000122	(0.01)	0.00297	(0.16)
Annual ave. 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	Y		Y		Y		Y	
Wave fixed effects	Y		Y		Y		Y	
State fixed effects	N		Y		N		Y	
Individual fixed effects	N		N		Y		Y	
R-squared	0.0949		0.0955		0.610		0.610	
F-stat (weather)	3.60		3.73		2.53		2.46	
F-stat (weather) p-value	0.0000		0.0000		0.0047		0.0061	
F-stat (climate)	6.97		9.19		0.68		0.25	
F-stat (climate) p-value	0.0000		0.0000		0.6089		0.9112	
N	96472		96472		96472		96472	

Notes: Individual clustered standard errors of mean in parentheses. *0.1 level, **0.05 level, ***0.01 level. 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, the natural log 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.

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