The Impact of Daily Weather Conditions on Life Satisfaction Evidence from Canadian Cross-sectional and Panel Data

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Abstract

Life satisfaction has been widely used in recent years for evaluating the effect of environmental factors on individuals' well-being. In this study, using two major health surveys in Canada, we show that after controlling for individuals' socioeconomic characteristics as well as local and seasonal climate, temporal weather variations have an impact on satisfaction with life. This effect is identified in a number of alternative specifications. Women and individuals with poor health condition are more affected by weather conditions. Although being statistically significant, the effect of weather on life satisfaction is small compared with major socioeconomic determinants of well-being. We cannot confirm the results of past studies which find an effect of long term climate variables on life satisfaction.

Keywords: life satisfaction, affect, income, climate, welfare, subjective well-being
APA code: **2340** Cognitive Processes
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1 Introduction

In recent years, the use of subjective measures of well-being has become widely accepted in economics, alongside the conventional objective well-being measures such as income, health and life expectancy. Psychologists have studied subjective well-being (SWB) measures such as life satisfaction (LS) for many years and have investigated their causes, correlates, and outcomes (Schwarz and Strack, 1991; Kahneman et al., 2003). SWB measures rely on individuals' own evaluation of their condition, which can be distinguished along two different dimensions. The first dimension is the cognitive, evaluative, or judgmental component of well-being, which is usually assessed with life satisfaction (LS). To measure LS, respondents are asked to evaluate their life "as a whole". The second dimension is the affect or the pleasure-pain component of well-being. Affective states mostly reflect positive and negative emotions at a given moment.

Economic studies use LS data to evaluate the effect of various determinants of well-being in the broad categories of income, personal and socially-developed individual characteristics, the pattern of time use, attitudes and beliefs, relationships, and the wider economic, social, and political environment (Dolan et al., 2008). There is also a growing amount of literature on more explicitly policy-relevant applications of the relation between LS and its determinants. Different studies in this area estimate the impact of government policies (Dolan et al., 2008; Diener, 2009) or evaluate social progress (on the Measurement of Economic Performance et al., 2009).

LS has also been used in a number of studies for the valuation of non-market goods such as environmental goods. Researchers have used the life satisfaction approach (LSA) to obtain the value of proximity to infrastructure (Brereton et al., 2008), air quality (Welsch, 2006; Rehdanz and Maddison, 2008; Luechinger, 2009; Levinson, 2012), and climatic conditions (Rehdanz and Maddison, 2005; Brereton et al., 2008; Maddison and Rehdanz, 2011). Additionally, the relationship between weather conditions and LS has been investigated by Barrington-Leigh (2009); Feddersen et al. (2012); Connolly (2013); Lucas and Lawless (2013).

1.1 Life satisfaction as a measure of utility

Recent progress made in the field of subjective well-being (SWB) reflects the need to move beyond the recognition of economic prosperity as the main determinant of well-being. Subjective well-being represents people's beliefs and feelings of whether they have a desirable life. More precisely, subjective well-being is a utility measure based on judgments of satisfaction, indicating individuals' evaluation of their own life along the two different dimensions of feelings and cognitions. While affect balance refers to the emotional reactions, moods, and momentary feelings a person has, life satisfaction refers to the cognitive judgments about one's life as a whole, typically over a longer period of time, and relates to what a person considers a good life to be.

Life satisfaction (LS) as a measure for individuals' well-being is obtained from respondents' answers to a question asking how satisfied they are with their life as a whole. According to Frey et al. (2010), for measures of SWB to serve as a proxy for individuals' welfare the following six conditions should be satisfied. The measures of SWB should: (1) be valid measures of individuals' welfare; (2) be broad and inclusive; (3) refer to respondents' present situation; (4) have small measurement errors, and no systematic ones; (5) be interpersonally comparable; and (6) be available at a sufficiently large scale (Frey et al., 2010). Their work contains an extensive discussion affirming that respondents' answers to the LS question in surveys mostly satisfy these conditions and provide a reliable measure of individuals' welfare.

If LS reports can be used as an empirically valid measure of individuals' utility, it is possible to directly find the impact of different variables affecting their welfare measured by this utility concept. LS is considered as a function of personal, socioeconomic and environmental characteristics related to the respondents. The respective relationship between LS, as a measure of experienced utility, and its determinants can be stated in the following form:

$$LS_{it} = f(x_{it},\, z_{it})$$

Individuals' well-being reported at the time of the interview (LS_{it}) depends on a number of personal and socioeconomic characteristics of individuals (x_{it}), as well as wider economic and local conditions, and environmental characteristics related to the respondents (z_{it}). In practice, the above function is considered to have an additively separable form (if it entails no interaction term) in which LS is explained by a weighted sum of all covariates. The OLS method then can be used to estimate the coefficients (weights) of this regression model.

In the Life satisfaction function, x_{it} and z_{it} represent individuals' personal attributes and the characteristics of their environment, respectively such as income, age, sex, marital status, level of education, and employment status as well as broader social and economic attributes of the location where respondents live. For a review of personal, social, and environmental factors influencing SWB and in particular life satisfaction see Dolan et al. (2008); MacKerron (2012); Helliwell and Barrington-Leigh (2010). Likely because these social and personal characteristics are relatively stable for an individual over time, LS scores demonstrate high to moderate stability over time (Fujita and Diener, 2005; Ehrhardt et al., 2000).

Although LS is mainly a measure to capture the cognitive and evaluative aspects of well-being, the judgments of well-being measured by LS are partly informed by, or sensitive to, recent transitory factors such as mood and priming of particular information (Schwarz et al., 1987). According to Frey et al. (2010) LS could be best described as a blend of cognitive judgment of life quality as a whole and responsiveness to transitory factors.

1.2 The impact of weather on individuals' life satisfaction

We now focus on the effect of weather variation as a transitory environmental condition on LS. The extent to which weather conditions affect reports of life satisfaction is important to quantify because it might influence the identification of the impact of a number of other factors affecting LS. If weather variables have a significant effect on LS, accounting for them is important when evaluating the effect of the LS determinants that are correlated with weather. For example, in the study of air pollution's impact on LS, controlling for the influence of weather is of great importance since weather is strongly correlated with air pollution (Luechinger, 2009, 2010; Levinson, 2012; Barrington-Leigh and Behzadnejad, 2016). Before we review the studies relating weather and LS, it is essential to discuss the channel through which weather affects the judgment of satisfaction by individuals.

A number of empirical studies show the impact of some recent events on the reported values of LS — for instance, time in a pleasant rather than an unpleasant room or when one's favorite team wins a game (Schwarz et al., 1987). Schwarz and Strack (1991) explain how individuals' moods at the time of judgment affect the reports of their LS. First, good moods increase the salience of recent positive events. So, happier individuals are likely to remember positive information and individuals in bad moods tend preferentially to remember negative information. When individuals think about their life as a whole, remembering good or bad aspects of it will lead to a higher or lower report of LS. Schwarz and Strack (1991) also state another, more direct, channel for the influence of moods: individuals might assume their well-being at the time of judgment to be a reasonable indicator of their general well-being. Thus, they might base their general satisfaction evaluation on their feelings at the time of the judgment and report a higher LS when they feel good. In essence, evaluating one's life as a whole is cognitively demanding and individuals might choose to refer to their current feelings at the time of the interview (Schwarz and Strack, 1991).

It should be noted that although mood variability affects the reporting of satisfaction with life, in general it does not have an impact on average LS in surveys. The reason is that the impacts from the transitory factors of this type are not correlated across individuals and idiosyncratic effects cancel each other out. In other words, when respondents appeal to their recent and current moods in order to estimate their LS, they do not change the sample average measures of LS because mood cycles are unlikely to be correlated across individuals.

An exception to this lack of correlation across individuals could arise from an influence such as weather, in which the "ups and downs" of people's affective cycles could be in phase. If responses in a sample were all taken during inclement weather, one might end up with an underestimate of the average LS. When weather is not considered in a sampling strategy and is not measured as a causal variable of interest, therefore, the question arises as to whether it could be biasing estimates. Even for large samples, well distributed across weather states, it is interesting to know the impact introduced by weather.

Weather is thought to constitute an example of a transient but identifiable influence on individuals' mood. The relation between mood and weather variables has been investigated in many studies. Keller et al. (2005) find a significant relation between pleasant weather (higher temperature or barometric pressure) and better mood, better memory, and broader cognitive style. Weather conditions have an impact on aspects of negative affect such as tiredness (Denissen et al., 2008). Respondents report being happier on sunny days versus rainy days (Schwarz and Clore, 1983). Although the relevant weather variables to individuals' mood vary across the mentioned studies, they show some associations between weather and mood.

The impact of weather on LS through affecting moods is the channel mentioned in most of the studies on the relation between LS and weather. Weather can have both a direct impact on mood or can affect mood through time spent in social and leisure activities (Connolly, 2008; Barrington-Leigh, 2009). Among all the studies on this subject only Barrington-Leigh (2009) has empirically tested whether individuals' mood is affected by weather variations. Using a four-level self-report measure of happiness, he finds no significant effect between happiness and temporal variation in weather. Considering the results of these works as a whole, more studies are required to further clarify the relation between moods and weather.

Finally, it is interesting to see whether weather also influences domain-specific satisfactions, such as satisfaction with health, job, and leisure activities. Schwarz and Strack (1991) discuss the issue of evaluating general LS versus domain-specific satisfaction. They declare that, as opposed to satisfaction with life as a whole, the evaluation of one's satisfaction in a specific area such as health or leisure activities may be cognitively less demanding and, as a result, may rely on more sustained or objective evidence, albeit interpreted with subjective criteria. Thus, it is expected for domain-specific satisfaction reports not to be influenced by transient factors such as weather.

1.3 Studies on the relation between life satisfaction and weather or climate

A number of studies concerning the relation between environmental factors and LS focus on the impact of long-term climate attributes on LS. 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 LS. Consistent with these studies, Feddersen et al. (2012) use a large panel of Australian data and detect a relationship between long-term climate and LS without individual fixed effects. However, they show that this relationship is not robust to individual fixed effects and conclude that climate has no direct influence on LS.

There are also a few studies on the effect of daily weather changes on LS. In essence, these studies find a statistically significant effect from a number of weather variables on LS. The size of the impact, however, is relatively small compared with major socioeconomic factors affecting well-being. Using two different Canadian surveys, Barrington-Leigh (2009) finds that recent cloud cover has a significant effect on LS. While mainly concerned about the air pollution impact, Levinson (2012) reports a significant effect of average daily temperature on LS. An increase in average temperature by one standard deviation increases the score of happiness on a three-point scale by 0.03. Connolly (2013) looks at the weather effect in a sample of 4000 adults surveyed in the US and finds that weather is only associated with LS in female respondents with negative significant impact of rain and high temperature. The LS scores measured on a scale from 1 to 4 is lower on a rainy day by 0.1 to 0.3 depending on the amount of rain.

Feddersen et al. (2012) use a large panel of Australian data to show that day-to-day variations of weather affect LS. They detect significant positive effects of daily solar exposure and negative effects of daily mean wind speed and sea-level air pressure at the time of the interview on LS. In this study, if total daily solar exposure is one standard deviation above its average, life satisfaction increases by 0.012 on an eleven-point scale. A one standard deviation change in mean sea level pressure and in daily wind speed increase LS by 0.016, and 0.026 respectively. Finally, using a repeated cross-sectional data set from the US, Lucas and Lawless (2013) show that while some monthly weather variables affect LS, the effect of daily weather conditions on life satisfaction is not statistically significant, and the effect of significant variables is very small.

1.4 Overview of findings

In this study, we look at the impact of daily variations in weather conditions on reported LS using two major health surveys in Canada: the CCHS (The Canadian Community Health Survey) and the NPHS (The National Population Health Survey). The main question of this study is as follows: Controlling for local and seasonal climate as well as individual fixed effects, does the day-to-day variation in weather influence LS in a meaningful way? We can account for individual fixed effects in the NPHS, which is a set of panel data including LS over four cycles.

Using both panel and crosssectional data sets is an advantage of this study over Barrington-Leigh (2009), which is the only study on the relation between weather and life satisfaction in Canada. Another advantage of the present study is related to accounting for geographic and seasonal fixed effects. In similar studies, the weather variables for each respondent are obtained using the nearest weather station to the respondent. Moreover, seasonal and geographic fixed effects are usually accounted for separately (Barrington-Leigh, 2009). In the present study, respondents are assigned to different month-stations, which are the interaction covariates of different stations with 12 months. The total number of month-station variables are then reduced using an algorithm that repeatedly drops month-stations with a small number of people and reassigns all the respondents.

Using OLS regression with our cross-sectional data or the pooled panel data, we find a negative and statistically significant impact of daily rainfall on LS. According to our preferred specification, if total daily rainfall is one standard deviation (6 mm) above its average, LS decreases by approximately 0.01 on a five-point scale with standard deviation 0.7. The robustness of these results is further investigated through testing a number of non-linear models. We next test whether there exists heterogeneity in the effect of weather across gender and health conditions. Females and individuals with poor health conditions are shown to be more sensitive to weather variation.

As mentioned earlier, psychological studies show that the cognitive complexity of thinking about LS can be a source of weather-related impacts in reporting this measure of well-being. To test this assumption in the present study, we look at the effect of weather variables on a different set of satisfaction measures. We estimate the weather impact on a number of domain-specific measures of well-being, such as satisfaction with health, job, and housing. These measures are assumed to be cognitively simpler to report compared to general LS. Similar to the results of Feddersen et al. (2012), we find that, considering all the regressions with domain-specific satisfactions, the total number of significant weather variables at 10% significant level is approximately equal to what is expected to be randomly significant. This suggests that on the whole, the effect of weather is not statistically significant while reporting less cognitively complex satisfaction measures.

LS data can be used to capture the well-being impacts from long-term local climate, as a stable environmental condition. In the last part of the paper, we show that, consistent with the literature on the impact of climate on LS, there is a relationship between long-term climate and LS in our cross-sectional data set. The effect of climate on LS in the estimations with our panel data is less evident. These results are similar to those of Feddersen et al. (2012) in both cross-section and panel analysis. So, it is possible that a number of omitted individual time-invariant characteristics have an impact both on people's selection of a living location and on their LS. However, more panel data analysis with larger samples of relocated individuals is needed to test for the direct impact of climate on LS.

The paper continues in section 2 with the explanation of the data sets used in the study and the discussion of the approach of our empirical analysis which aims to isolate the "unexpected" component of the daily weather. The results of different estimations along with the discussion of the results are presented in section 3. Section 4 concludes.

2 Data and Methodology

The main data sets used in this study are the Canadian National Population Health Survey (NPHS) and the Canadian Community Health Survey (CCHS), as well as weather data and air quality data obtained from Environment Canada. A summary of variables is contained in Tables A.4 and A.5.

The NPHS consists of a panel of individuals set up in 1994. It provides health data as well as economic, social, demographic, occupational and environmental information correlated with health for a representative sample of Canadians. The analysis of such a data set provides valuable information on the dynamics of health-related issues over time. In this study we consider the last four cycles of the NPHS, from 2004 to 2010, which contain the LS question.

The CCHS collects cross-sectional information on health-care status, health determinants, and many other variables related to health in addition to the usual demographic information from a large sample of Canada's population on a nearly-annual basis. Our analysis relies on the six recent cycles of 2005 to 2011; there was no survey in 2006. The question relevant to LS in the NPHS and the CCHS is the following: "How satisfied are you with your life in general?" Respondents chose from one of the five levels (or eleven levels in the last three cycles of the CCHS) of satisfaction, which ranged from very satisfied to very dissatisfied. After pooling respondents from all cycles, LS scores with eleven-points scales are mapped into the five-point scale scores.

Daily and hourly weather data as well as long-term climate averages are available online from the Environment Canada data server. Environment Canada collects these data from roughly 2100 stations throughout the country. Daily and almanac data on temperature and precipitation are available at most of these stations. A number of stations provide hourly data including sky condition, which is used to derive daily and weekly cloud cover variables.[1]

To obtain the weather and climate variables for each respondent, both surveys are combined with the weather and climate data sets. The date of the interview and the postal code of the respondents are available in the confidential microdata versions of the CCHS and the NPHS. Having the geographic coordinates as well as the date of the interview, it is possible to find the weather information of the stations close to each respondent.

In the specifications with no control for geographic fixed effects, individuals are assigned to the nearest weather station(s). However, in most of our specifications, it is necessary to account for the seasonal and geographic fixed effects at the same time. Barrington-Leigh (2009) uses

[1] The description reflecting the observation of total cloud amount is coded to numerical values. Clear, mainy clear, mostly cloudy, and cloudy sky conditions are coded to 0,1,2,3 respectively. Daily cloud cover is then the average cloud cover for 12 hours of the day.

a heuristic method to optimally assign individuals to nearby stations and reduce the total number of stations at the same time. In the algorithm used by Barrington-Leigh (2009), all the individuals are assigned to the nearest station and then stations with only a small number of individuals assigned to them are dropped. The process is repeated with a decreasing number of stations.

An improvement to this algorithm, which is used in our analysis, accounts for the seasonal and the geographic fixed effects at the same time. In this algorithm, the dropping criterion combines the month of interview with the station, so that only station-month pairs with a low number of assignees are dropped in each cycle. More precisely, at each stage the individuals are assigned to the nearest station-month that has the same month as the interview month. The station-months with fewer than 10 respondents are then dropped. The cycle is repeated three times. At the end, individuals living farther than 30 km from the nearest remaining station are dropped. Lastly, the individuals in station-months with fewer than eight individuals are dropped.

In the station-month algorithm, a number of stations with fewer respondents are dropped in favor of the stations with more respondents assigned to them. So, one concern might be that the distance of the respondents to the monitoring stations increases in the station-month algorithm compared to the nearest station algorithm. However, it should be noted that the relative number of missed observations resulting from the station-month assignment algorithm is not very high (0.7% in the CCHS and 9% in the NPHS). Additionally, according to Hubbard (1994), for most of weather variables, more than 90% of variations at a given location can be explained by the data recorded in a spacing of approximately 30 km. Therefore, as long as the distance between a respondent and a monitoring station is less than 30 km, which is the case in our study, the weather information is close enough to what is experienced by the respondent.

To estimate the effect of weather variables on LS, controlling for location-specific seasonal effects, the following reduced form equation is used:

$$LS_{ijt} = X_{it}^{'}\gamma + W_{jt}^{'}\beta + l_j + y_t + m_t + u_i + \epsilon_{ijt}$$

In this equation, LS_{ijt} is the LS of individual i at the location j at time t. X_{it} is the vector of socioeconomic characteristics of individual $i.W_{jt}$ is a vector of weather variables related to the day and location of the interview. y_t represents a set of dummies for the year, and thus accounts for the effect of year-specific shocks. Similarly, m_t accounts for month fixed effects and controls for seasonal variation in LS. Variable l_j is a set of dummies to control for the location of the respondents. u_i, which is a part of the model only in estimating the coefficients with the panel data, is a dummy variable representing individual fixed effects.

The above specification is used when controlling separately for location and the interview month of respondents. However, since the respondents are assigned into station-month groups in most of the specifications in this study, it is preferred to account for station-month dummies instead of a separate control for month and location. The station and month dummies in the above model are then replaced by $(st-m)_{jt}$ which is a set of dummies representing the station and the interview month of respondents.

3 Results

Table 1 is related to the first attempt to estimate the effect of weather on LS. Each specification contains weather variables obtained from the nearest weather station to the respondents. All the regressions also include a set of variables controlling for the socioeconomic characteristics of individuals. These characteristics include log of household income, age, age squared, and a set of dummy variables for sex, education, marital status, and employment status. The columns show the results of the estimation on the CCHS, the NPHS, and the NPHS pooled sample. While we control for individual fixed effects in the estimations using the NPHS as a panel data set, in the estimation of the NPHS pooled sample there is no accounting for individual fixed effects.

The first six columns show the estimated coefficients of the models with only daily rain or recent cloudiness measured by the cloudiness in the week prior to the interview. Recent cloudiness is the variable that was found to have an effect on LS in the study of Barrington-Leigh (2009) using a much smaller sample of Canadian data. The estimation results for the impact of the other weather variables are displayed in Table A.1 in the appendix. Column 1 shows an almost significant effect of daily rain on LS in the CCHS sample. The effect of rain is similar (but not significant) in the NPHS with individual fixed effects. In fact, none of the weather variables has a significant effect on LS in the NPHS sample with a control for individual fixed effects. In the NPHS pooled sample daily cloudiness, difference in maximum and minimum temperature, and daily snow seem to be statistically significant when each is considered in a separate regression (Table A.1). Columns 7–9 report results from estimations with all the weather variables at the same time. Apart from daily rain with an almost significant coefficient in the CCHS sample, there is no evidence for the significant effect of weather variables in the CCHS or in the NPHS panel estimate and only snow remains significant in the NPHS pooled estimate.

The coefficients of daily weather variables may be biased when there is no control for time-invariant local fixed effects. Controlling for geographic fixed effects eliminates the confounding

Table 1: Weather and life satisfaction, without geographic controls

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS
T_{max}-T_{min}($^{\circ}C$)							0.0004	-0.0046	-0.0024
							(0.36)	(-14.)	(-0.93)
T_{mean}($^{\circ}C$)							-0.0003	-0.0004	-0.0011
							(-0.87)	(-0.25)	-(0.31)
rain (mm)	-0.0009	-0.0008	-0.0005				-0.0009	-0.0015	-0.0011
	(-1.6)	(-0.69)	(-0.41)				(-1.60)	(-1.11)	(-0.80)
snow (cm)							-0.0005	0.0053	0.0072*
							(-0.25)	(1.19)	(1.80)
cloud							0.0030	-0.0050	0.0148
							(0.44)	(-0.29)	(0.87)
cloud (7 days)				-0.0004	0.0180	0.026	0.0017	-0.0074	0.0243
				(-0.06)	(0.83)	(1.6)	(0.15)	(-0.21)	(0.86)
log (HH income)	0.160***	0.090***	0.197***	0.157***	0.085***	0.193***	0.159***	0.0925***	0.1997***
	(28.6)	(3.84)	(14.8)	(32.7)	(4.14)	(16.1)	(27.3)	(3.77)	(14.5)
Constant	3.00***	3.32***	2.73***	3.03***	3.30***	2.80***	2.99***	3.35***	2.72***
	(41.1)	(12.2)	(16.0)	(47.9)	(13.8)	(17.9)	(38.1)	(11.4)	(14.8)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	141830	11629	13018	182893	14394	16086	132371	10909	12223
R^2	0.073	0.681	0.072	0.071	0.672	0.073	0.073	0.686	0.074

*** statistically significant at 1%. ** statistically significant at 5%. * statistically significant at 10%.
t-statistic appears bellow each coefficient.
Standard errors are clustered at the Station level (Station-month level if station-month groups are used to control for geographic fixed effects).

of the effect of weather with location-specific variables and helps to isolate the effect of transient weather variations, which may then be thought of as a natural experiment. Table 2 includes the same specifications as those in Table 1, but controls for location fixed effects using a set of dummies for all the weather stations. Similar to Table 1, daily rain has a significant effect on LS in the CCHS sample. This is true for the specification with only one weather variable as well as the one that contains all the weather variables. The daily rain coefficient has a similar (but not statistically significant) value in the NPHS sample with individual fixed effects. As can be seen in columns 3 and 9 of Table A.2 in the appendix, temperature difference and cloudiness are also statistically significant in the specifications with only one weather variable.

Table 2: Weather and life satisfaction, allowing for local fixed effects

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS
T_{max}-T_{min}($^{\circ}C$)							-0.0007	-0.0046	-0.0039
							(-0.55)	(-1.4)	(-1.2)
T_{mean}($^{\circ}C$)							0.0002	-0.0004	-0.0004
							(0.51)	(-0.36)	(-0.28)
rain (mm)	-0.0010**	-0.0008	-0.0011				-0.0014***	-0.0014	-0.0020
	(-2.1)	(-0.84)	(-1.0)				(-2.9)	(-1.1)	(-1.4)
snow (cm)							-0.0013	0.0051	0.0046
							(-0.74)	(1.3)	(0.98)
cloud							0.0008	-0.0052	0.0142
							(0.11)	(-0.29)	(0.63)
cloud (7 days)				-0.0081	0.0071	0.055***	-0.0066	-0.013	0.022
				(-0.84)	(0.26)	(0.81)	(-0.52)	(-0.29)	(0.66)
log (HH income)	0.166***	0.0913***	0.212***	0.163***	0.0815***	0.208***	0.165***	0.0936***	0.214***
	(17.3)	(3.51)	(13.9)	(21.4)	(3.82)	(15.2)	(16.8)	(3.31)	(13.42)
Constant	2.96***	3.35***	2.67***	2.99***	3.17***	2.73***	2.96***	3.38***	2.67***
	(34.4)	(11.7)	(15.5)	(39.6)	(12.9)	(16.0)	(31.2)	(10.7)	(13.3)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	141830	11629	13018	182893	14394	16086	132371	10909	12223
R^2	0.080	0.686	0.092	0.079	0.678	0.096	0.080	0.691	0.095

See the footnotes to Table 1.

3.1 A natural experiment for daily weather conditions

To control for the seasonal variations in LS, month fixed effects should also be considered in addition to geographic fixed effects. This eliminates confounding the season-related factors with weather at the day of the interview. Thus, a set of dummy variables representing the station-month combination of the respondents' locations and interview dates are considered. In addition, the individuals are clustered into station-month groups using the algorithm explained in detail in the data section. We also use station-month groups as clusters in the error structure.[2] Tables 3 and A.3 report the results of the estimation of the model with station-month fixed effects and clustering. As can be seen in column 1 of Table 3, the coefficient of daily rain is significant in the CCHS when rain is the only weather variable. In addition, the rain coefficient is also significant in columns 7 and 9 with all the weather variables. In the NPHS with individual fixed effects, the daily rain coefficients have similar values as those in the CCHS, but these coefficients are not significant. In contrast to the results of Barrington-Leigh (2009), the impact of recent cloudiness, as estimated in columns (4-6), is not significantly different from zero. According to columns 7 and 8, increasing daily rainfall by one standard deviation (6 mm) will decrease LS by 0.008 in the CCHS and 0.011 in the NPHS, where LS is measured from one to five in both surveys.

In order to compare the effect of weather variables with that of the other covariates, the coefficients of all the socioeconomic variables are displayed in Table 4. Columns (1-3) and (10-12) of Table 4 are identical to columns (1-3) and (7-9) of Table 3 except that they also show the coefficients of all the socioeconomic variables not displayed in Table 3.

3.2 Does weather bias estimates of the determinants of life satisfaction?

Compared to some of the major determinants of LS, the marginal effect of the weather variables on LS is small. On a scale from 1 to 5, the marginal effect of daily rainfall on LS is small relative to being married (0.15 in the CCHS, 0.08 in the NPHS), being separated from a partner (-0.08 in the CCHS, -0.18 in the NPHS), or permanently being unable to work (-0.48 in the CCHS, -0.01 in the NPHS). Considering the income coefficient in the CCHS, a 1% increase in household income is associated with a 0.0016 increase in LS. So, the marginal effect of day-to-day variations of rainfall is similar to the effect of a 1% change in household income.

It is interesting to address the possible bias of not including weather variables in the estimation of LS. Columns (4-6) of Table 4 include only weather variables. In contrast, columns (7-9)

[2]Using station-level (rather than station-month) error clustering when our controls include station-month fixed effects makes little difference to standard errors. We also tested for the role of spatial correlation by testing our regressions with a spatial error model. Because daily weather varies more over time than across even nearby stations, standard errors were essentially unchanged by allowing for spatial correlation. Details available from the authors.

Table 3: Weather and life satisfaction, allowing for local seasonal fixed effects

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS
T_{max}-$T_{min}(^\circ C)$							-0.0004	-0.0004	-0.0016
							(-0.28)	(-0.17)	(-0.50)
$T_{mean}(^\circ C)$							-0.0009	-0.0005	0.0019
							(-1.18)	(-0.27)	(0.89)
rain (mm)	-0.0010*	-0.0007	-0.0009				-0.0013**	-0.0019	-0.0026*
	(-1.9)	(-0.56)	(-0.73)				(-2.2)	(-1.3)	(-1.7)
snow (cm)							-0.0017	0.0055	0.0039
							(-0.90)	(1.0)	(0.71)
cloud							0.0030	0.043	0.0253
							(0.41)	(0.80)	(1.40)
cloud (7 days)				0.0019	0.0343	0.0679***	-0.0019	0.0277	0.0503
				(0.18)	(1.5)	(2.7)	(-0.142)	(0.89)	(1.6)
log (HH income)	0.166***	0.0748***	0.214***	0.163***	0.0715***	0.208***	0.164***	0.0799***	0.218***
	(27.8)	(3.05)	(13.1)	(32.0)	(3.41)	(13.5)	(26.4)	(3.1)	(12.8)
Constant	2.97***	3.57***	2.61***	2.99***	3.47***	2.64***	2.97***	3.51***	2.52***
	(38.8)	(10.9)	(11.4)	(44.1)	(12.0)	(12.4)	(34.8)	(10.)	(10.5)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	140903	10488	11835	181485	12701	14321	131553	9841	11124
R^2	0.089	0.706	0.123	0.090	0.703	0.127	0.089	0.712	0.126

See the footnotes to Table 1.

contain only non-weather covariates. Comparing the no-weather specifications with the last three columns shows that controlling for the weather variables seems not to change most of the coefficients of non-weather covariates much. The statistically significant coefficients are approximately the same among the two sets. However, a number of coefficients such as those for being absent from work last week have different values in the two sets of columns. Nevertheless, the size of the weather bias in the estimation of the impact of the LS determinants considered in our model is mainly negligible. Similarly, controlling for individual-specific variables in the last three columns does not alter the weather coefficients to a great extent compared to columns (4-6) with only weather variables.

Table 4: Weather and life satisfaction, allowing for local seasonal fixed effects (extended table)

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS	(10) LS	(11) LS	(12) LS
Age	-0.024***		-0.028***				-0.025***		-0.031***	-0.024***		-0.031***
	(-15.)		(-6.5)				(-19.)		(-7.7)	(-14.)		(-6.8)
Age squared	0.0002***		0.0003***				0.0002***		0.0003***	0.0002***		0.0003***
	(13.)		(6.3)				(18.)		(7.6)	(13.)		(6.7)
Female	0.047***		0.031				0.048***		0.030*	0.047***		0.037*
	(7.1)		(1.5)				(8.6)		(1.76)	(6.7)		(1.7)
Married	0.16***	0.13**	0.21***				0.16***	0.020	0.23***	0.15***	0.085	0.21***
	(13.)	(2.0)	(6.7)				(18.)	(0.42)	(8.6)	(12.)	(1.3)	(6.2)
Common-law	0.10***	0.13**	0.17***				0.11***	0.11**	0.18***	0.10***	0.13*	0.16***
	(8.5)	(2.2)	(4.96)				(11.)1	(2.3)	(6.5)	(7.4)	(1.7)	(4.3)
Widowed	0.0047	0.013	0.063				0.0005	-0.11	0.054	-0.0096	-0.0096	0.065
	(-0.23)	(0.09)	(1.1)				(0.029)	(0.84)	(1.1)	(-0.44)	(-0.062)	(1.1)
Separated	-0.075***	-0.16	-0.035				-0.080***	-0.22***	-0.077	-0.085***	-0.18*	-0.037
	(-3.5)	(-1.6)	(-0.66)				(-4.2)	(-2.7)	(-1.5)	(-3.9)	(.67)	(-0.66)
Divorced	0.0008	0.12	0.10**				-0.0096	0.10	0.11***	-0.0058	0.12	0.10**
	(0.05)	(1.3)	(2.0)				(-0.71)	(1.1)	(2.7)	(-0.34)	(1.1)	(2.0)
Work last week	0.028	-0.11*	0.13*				0.046***	0.062	0.15**	0.026	-0.094	0.156**
	(1.6)	(-1.7)	(1.9)				(3.20)	(0.98)	(2.5)	(1.4)	(-1.4)	(2.4)
Absent last week	0.059**	-0.21***	0.031				0.045**	-0.031	0.070	0.065**	-0.21***	0.063
	(2.4)(	(-2.8)	(0.41)				(2.2)	(-0.45)	(1.1)	(2.5)	(-2.7)	(0.82)
No job last week	0.0018	-0.13**	0.14**				0.015	0.036	0.15***	-0.0021	-0.13*	0.16***
	(0.12)	(-2.1)	(2.5)				(1.2)	(0.63)	(3.1)	(-0.13)	(-2.0)	(2.74)
Perm. unable	-0.48***	-0.036	-0.14				-0.46***	-0.34	-0.22**	-0.48***	-0.015	-0.11
	(-15.)	(-0.32)	(-1.2)				(-17.)	(-0.39)	(-2.3)	(-15.)	(-0.14)	(-0.97)
Secondary	0.088***	0.031	0.032				0.092***	0.026	0.016	0.092***	0.0076	0.048
	(4.0)	(0.30)	(0.80)				(5.4)	(0.31)	(0.48)	(3.8)	(0.07)	(1.15)
Other post sec.	0.065***	-0.026	0.0065				0.062***	-0.015	-0.0016	0.068***	-0.028	0.031
	(2.7)	(-0.28)	(0.19)				(3.25)	(-0.189)	(-0.06)	(2.65)	(-0.28)	(0.85)
Post sec. grad.	0.088***	0.014	0.021				0.086***	0.063	0.016	0.07***	-0.022	0.038
	(4.1)	(0.14)	(0.589)				(5.3)	(0.72)	(0.55)	(4.2)	(-0.21)	(0.99)
log (HH income)	0.166***	0.0748***	0.214***				0.163***	0.0717***	0.196***	0.165***	0.0799***	0.218***
	(27.8)	(3.05)	(13.1)				(34.8)	(3.75)	(13.4)	(26.4)	(3.07)	(12.8)
T_{max}-T_{min}($^{\circ}C$)				-0.0009	-0.0010	-0.0004				-0.0004	-0.0004	-0.0016
				(-0.67)	(-0.46)	(-0.12)				(-0.28)	(-0.17)	(-0.50)
T_{mean}($^{\circ}C$)				-0.0012	-0.0005	0.0013				-0.0009	-0.0005	0.0019
				(-1.5)	(-0.27)	(0.58)				(-1.2)	(-0.27)	(0.89)
snow (cm)				-0.0016	0.0056	0.0036				-0.0017	0.0055	0.0039
				(-0.89)	(1.0)	(0.62)				(-0.90)	(1.0)	(0.701)
rain (mm)	-0.0010*	-0.0007	-0.0009	-0.0014**	-0.0020	-0.0027*				-0.0013**	-0.0019	-0.0026*
	(-1.9)	(-0.56)	(-0.73)	(-2.1)	(-1.4)	(-1.8)				(-2.2)	(-1.3)	(-1.7)

VARIABLES	(1) **LS**	(2) **LS**	(3) **LS**	(4) **LS**	(5) **LS**	(6) **LS**	(7) **LS**	(8) **LS**	(9) **LS**	(10) **LS**	(11) **LS**	(12) **LS**
cloud				**0.0039** **(0.53)**	**0.012** **(0.67)**	**0.031*** **(1.7)**				**0.0030** **(0.41)**	**0.014** **(0.80)**	**0.025** **(1.4)**
cloud (7 days)				**-0.0039** **(-0.28)**	**0.023** **(0.73)**	**0.043** **(1.4)**				**-0.0019** **(-0.14)**	**0.028** **(0.89)**	**0.050** **(1.56)**
Constant	**2.78***** **(42.2)**	**3.55***** **(11.4)**	**2.27***** **(11.4)**	**4.31***** **(202.)**	**4.30***** **(23.0)**	**4.21***** **(46.2)**	**2.81***** **(53.6)**	**3.45***** **(13.1)**	**2.45***** **(14.0)**	**2.80***** **(37.1)**	**3.51***** **(10.8)**	**2.15***** **(10.33)**
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Socioecon. covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Stn-month fix. effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	140903	10488	11835	131553	9841	11124	206859	14073	15880	131553	9841	11124
R^2	0.089	0.706	0.123	0.016	0.709	0.058	0.091	0.686	0.121	0.089	0.712	0.126

See the footnotes to Table 1.

According to the above analysis, inclusion of weather variables is not of great importance for estimating the effect of the recognized socioeconomic determinants of LS. However, since weather has a statistically significant impact on LS, considering weather is crucial when estimating the effect on LS of variables that are correlated with weather. Studies in the recently growing literature on the effect of environmental factors on LS need to consider weather variables in order to report unbiased coefficients for the variable of interest if the environmental factors are correlated with weather. For example, models of the impact of air pollution on LS include weather variables (Luechinger, 2009, 2010; Barrington-Leigh and Behzadnejad, 2016).

3.3 Specification tests

Table 5 presents results from the estimation of some alternative models. All the specifications control for year and station-month fixed effects as well as for all the demographic and socioeconomic variables considered in Table 3. We estimate three different models to test for non-linear effects of weather on LS. The first model contains the weather variables as well as the squared weather terms. According to the results of estimating this model in columns (1-2) of Table 5, there is no evidence of a non-linear effect for any of the variables in the CCHS sample. In the NPHS sample, significant coefficients of rain squared indicate the larger effect of higher amounts of rainfall in reducing LS within an individual.

Another way to test for non-linearity in the impact of weather covariates is to consider the estimation of the log of LS on the weather variables and the rest of the covariates. This specification accounts for an exponential effect of variables on LS. As can be seen in column 2 of Table 5, in line with the results of the previous estimations, daily rain has a significant effect on LS in the CCHS sample.

Due to the ordinal scale of LS scores, ordered discrete choice models such as ordered probit have been used by researchers. However, most of the studies that use both OLS and ordered probit find little difference between the results of the two models (Ferrer-i Carbonell and Frijters, 2004). One advantage of OLS over ordered probit is that OLS easily accommodates all types of fixed effects, including individual fixed effects. As displayed in column 3 of Table 5, daily rain is again the only weather variable with a significant effect on LS in the ordered probit model. The marginal effect of daily rainfall on LS is not significantly different from what was estimated with the OLS method in the baseline specification (Table 3, column 7).

3.4 Weather and gender

Next, we test whether heterogeneous weather effects arise across gender and health conditions. Feddersen et al. (2012) and Connolly (2013) look at the effect of weather on males and females

Table 5: Testing for non-linear effects of weather on life satisfaction

VARIABLES	(1) LS	(2) ln(LS)	(3) LS	(4) LS	(5) ln(LS)
T_{max}-T_{min}($^{\circ}C$)	-0.0042	-0.0001	-0.0010	-0.0097	-0.0001
	(-1.0)	(-0.21)	(-0.45)	(-1.4)	(-0.18)
T_{mean}($^{\circ}C$)	-0.0008	-0.0003	-0.0011	-0.0002	0.0000
	(-1.0)	(-1.4)	(-0.8)	(-0.09)	(0.08)
rain (mm)	-0.0020	-0.0003**	-0.0023**	0.0031	-0.0004
	(-1.6)	(-2.0)	(-2.2)	(1.2)	(-1.1)
snow (cm)	-0.0056	-0.0005	-0.0023	0.019**	0.0016
	(-1.4)	(-0.99)	(-0.73)	(2.1)	(1.1)
cloud	-0.014	0.0010	0.0040	0.072*	0.0024
	(-0.68)	(0.46)	(0.33)	(1.9)	(0.47)
cloud (7 days)	0.029	-0.0004	-0.0078	0.050	0.0071
	(0.62)	(-0.11)	(-0.33)	(0.47)	(0.73)
$(T_{max} - T_{min})^2$	0.0002			0.0004	
	(1.0)			(1.5)	
$(T_{mean})^2$	-0.0000			-0.0001	
	(-0.04)			(-0.90)	
rain^2	.0000			-0.0001*	
	(0.51)			(-1.8)	
snow^2	0.0002			-0.0007*	
	(1.3)			(-1.9)	
cloud^2	0.0087			-0.036*	
	(0.93)			(-1.8)	
cloud (7 days)^2	-0.016			-0.014	
	(-0.72)			(-0.27)	
log (HH income)	0.166***	0.0454***	0.280***	0.0800***	0.0265***
	(26.8)	(25.9)	(26.7)	(3.08)	(3.27)
Constant	2.44***	0.931***		3.53***	1.17***
	(30.6)	(43.5)		(10.3)	(11.3)
Individual fixed effects	N	N	N	Y	Y
Socioeconomic covariates	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y	Y
Survey	CCHS	CCHS	CCHS	NPHS	NPHS
Observations	131553	131553	131553	9841	9841
R^2	0.082	0.082		0.713	0.693

See the footnotes to Table 1.

in Australia and the USA respectively. Feddersen et al. (2012) find that each gender group responds to different weather variables. In their study, while both males and females are responsive to mean sea-level air pressure, men are more sensitive to daily solar exposure and women are more sensitive to wind speed. Connolly (2013) finds high temperature and daily rain to affect women's LS. Neither of the weather variables is found to be significantly different from zero for men in her study. The first two columns of Table 6 display the results of estimating weather effects for only male respondents and columns (3-4) are related to female respondents. As can be seen in columns 1 and 3 of Table 6, while none of the weather variables have a significant effect on males' satisfaction in the CCHS sample, the LS of females is responsive in a meaningful way to the amount of daily precipitation in both rain and snow forms. Additionally, the coefficient of rain for females is significantly different from the males' coeffecient. None of the weather variables' effects is found to be significantly different from zero when individual fixed effects are accounted for in the NPHS sample.

3.5 Weather and health

One channel through which temporal variations of weather might have an impact on well-being is by affecting individual's health or symptoms related to health conditions. Various diseases and disorders are linked with weather extremes. For example, Braga et al. (2002) show the acute effects of weather on respiratory and cardiovascular diseases by carrying-out time-series analyses in 12 US cities. Individuals with worse health conditions are probably more affected by unfavorable weather conditions. In order to test whether there is a difference in the effect of weather depending on the respondents' health conditions, we use the Health Utilities Index or HUI, which is available in both the CCHS and the NPHS. This measure of health provides a description of individuals' overall functional health. HUI is based on eight different attributes: vision, hearing, speech, ambulation (ability to get around), dexterity (use of hands and fingers), emotion (feelings), cognition (memory and thinking), and pain. The range of this index is from -0.36 for the worst health status to 1 for perfect health status. Table 7 shows the results of the specification for individuals with different health status. Columns 1 and 3 are related to respondents with good to perfect health (HUI$>$0.5), and columns 2 and 4 are for respondents with bad to severe health status (HUI$<$0.5).

Higher coefficients (in absolute value) of weather variables in columns 2 and 4 indicate that respondents with health problems are more affected by weather conditions. In the CCHS sample, the only significant variable is rain with an impact similar to that obtained for the whole sample in Table 3. The effect of rain is much higher (but not significant) for the poor health group. When individual fixed effects are accounted for, there is no significant effect of weather on the healthier group. As can be seen in the last column of Table 7, the effect of daily rain and cloud is higher and statistically significant for the poor health category.

Table 6: The effect of weather on life satisfaction for males vs. females

VARIABLES	(1) LS (Males)	(2) LS (Males)	(3) LS (Females)	(4) LS (Females)
T_{max}-T_{min}($^{\circ}C$)	-0.0025	0.0001	0.0017	0.0007
	(-1.5)	(0.03)	(0.95)	(0.20)
T_{mean}($^{\circ}C$)	-0.0015	0.0006	0.0000	-0.0022
	(-1.3)	(0.19)	(0.006)	(-1.1)
rain (mm)	-0.0004	-0.0026	-0.0022***	-0.0007
	(-0.460)	(-1.2)	(-2.8)	(-0.41)
snow (cm)	0.0007	0.0073	-0.0047**	0.0043
	(0.23)	(1.1)	(-2.1)	(0.53)
cloud	-0.0066	0.020	0.012	0.0025
	(-0.649)	(0.869)	(1.095)	(0.098)
cloud (7 days)	-0.016	0.033	0.014	0.036
	(-0.79)	(0.69)	(0.78)	(0.92)
log (HH income)	0.165***	0.0530	0.164***	0.107***
	(17.4)	(1.37)	(21.5)	(3.33)
Constant	3.15***	3.78***	2.57***	2.82***
	(24.5)	(7.03)	(19.7)	(7.32)
Individual fixed effects	N	Y	N	Y
Socioeconomic covariates	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y
Survey	CCHS	NPHS	CCHS	NPHS
Observations	61753	4440	69800	5401
R^2	0.103	0.717	0.096	0.735

See the footnotes to Table 1.

Table 7: The effect of weather on life satisfaction for individuals with different health status

VARIABLES	(1) LS (HUI>0.5)	(2) LS (HUI<0.5)	(3) LS (HUI>0.5)	(4) LS (HUI<0.5)
T_{max}-T_{min}($^{\circ}C$)	-0.0004	-0.0066	0.0001	0.023
	(-0.35)	(-0.55)	(0.05)	(1.04)
T_{mean}($^{\circ}C$)	-0.0004	-0.022***	-0.0007	-0.0025
	(-0.55)	(-2.9)	(-0.36)	(-0.17)
rain (mm)	-0.0013**	-0.0051	-0.0018	-0.028***
	(-2.2)	(-0.99)	(-1.2)	(-3.0)
snow (cm)	-0.0014	-0.026	0.0042	0.0025
	(-0.82)	(-1.16)	(0.84)	(0.12)
cloud	0.0007	0.083	0.017	0.32**
	(0.10)	(1.2)	(0.94)	(2.2)
cloud (7 days)	0.0028	-0.17	0.017	-0.3
	(0.21)	(-1.2)	(0.54)	(-1.4)
log (HH income)	0.161***	0.162**	0.0707***	0.604***
	(26.)	(2.4)	(2.6)	(3.26)
Constant	3.00***	3.17***	3.69***	-2.60
	(36.)	(3.4)	(11.)	(-1.2)
Individual fixed effects	N	N	Y	Y
Socioeconomic covariates	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y
Survey	CCHS	CCHS	NPHS	NPHS
Observations	128564	2989	9298	543
R^2	0.082	0.367	0.710	0.944

See the footnotes to Table 1.

3.6 Cognitive complexity of subjective well-being reports

It is often claimed by psychologists that the complexity of the task of reporting a global judgment is a source of bias in evaluating LS. Respondents usually only form the global judgments needed to answer the LS question when asked. Answering the general satisfaction question needs a cognitive process which involves memory, comparison, and aggregation. This complex process necessitates using available information to assess one's overall status, and one easily accessible class of information is current mood and recall of recent moods, which are both reflective of transient factors in addition to representing longer-term influences (Schwarz and Strack, 1991). Weather variables are among the transient factors shown to affect individuals' mood in psychological studies (Keller et al., 2005).

A number of the surveys containing the satisfaction with life question also ask about satisfaction in some domain such as health, job, and leisure. In contrast to LS evaluation, assessing the specific life domains is less cognitively demanding, since comparison information is relatively more available and criteria for evaluation are relatively well constrained (Schwarz and Strack, 1991). For instance, the evaluation of satisfaction with one's financial situation is most probably more straight forward than evaluating one's life in general.

A number of domain-specific satisfaction questions are posed to a sub-sample of the CCHS respondents. Table 8 shows the results of the estimation of our preferred model (column 7 of Table 3) using the measures of satisfaction with health, job, leisure, friends, neighborhood, financial situation, and housing. According to Table 8 the variable for rain is again statistically significant in the specifications with health, job and financial situation as the dependent variable. In terms of the magnitude of the rain coefficient, we cannot reject the coefficients are different from the rain coefficient in our most preferred regression with life satisfaction. In general, based on the results in Table 8 it is hard to derive evidence consistent with the idea that domain-specific satisfactions are less prone to be affected by transient factors such as weather.

3.7 Climate effects

Up to now, we have looked at the effect of transitory weather on LS. A number of studies such as Rehdanz and Maddison (2005) and Maddison and Rehdanz (2011) show significant effects of climate with data sets at the country level. Using individual-level data, Brereton et al. (2008) and Feddersen et al. (2012) find a significant effect of climate on individuals' LS. However, in their study there is no significant effect of climate on LS in the specifications with individual fixed effects.

If seasonal or geographic variation is not considered in the model, there will be a bias in the estimation of the coefficients of transient weather variables. The reason is that the seasonal

Table 8: Weather and domain specific satisfaction

VARIABLES	(1) Health satisfaction	(2) Job satisfaction	(3) Leisure satisfaction	(4) Friend satisfaction	(5) Neighbors satisfaction	(6) Financial satisfaction	(7) Housing satisfaction
T_{max}-$T_{min}(^{\circ}C)$	0.0006	0.0031	0.0011	-0.0036	0.0016	-0.0032	-0.0040*
	(0.40)	(0.96)	(0.40)	(-1.6)	(0.674)	(-0.86)	(-1.7)
$T_{mean}(^{\circ}C)$	-0.0006	0.0021	0.0044*	0.0022	0.0017	0.0030	0.0006
	(-0.56)	(0.78)	(1.9)	(1.4)	(0.79)	(1.2)	(0.31)
rain (mm)	-0.0015*	-0.0031*	-0.0004	-0.0012	0.0003	-0.0029*	-0.0005
	(-1.86)	(-1.79)	(-0.23)	(-0.96)	(0.21)	(-1.7)	(-0.35)
snow (cm)	0.0004	0.0055	0.0019	0.0031	0.0054	-0.0025	-0.0003
	(0.16)	(1.6)	(-0.024)	(0.87)	(1.4)	(-0.66)	(-0.079)
cloud	0.016	0.0086	0.041*	-0.0051	-0.0060	-0.0088	0.014
	(1.4)	(0.43)	(1.80)	(-0.42)	(-0.35)	(-0.44)	(-1.12)
cloud (7 days)	0.010	0.027	-0.035	-0.033	-0.012	-0.022	-0.013
	(0.539)	(0.98)	(-1.2)	(-1.2)	(-0.42)	(-0.61)	(-0.49)
log (HH income)	0.179***	0.159***	0.163***	0.0967***	0.147***	0.395***	0.195***
	(24.3)	(12.8)	(11.9)	(9.73)	(11.9)	(23.1)	(16.7)
Constant	2.03***	0.684***	2.82***	3.49***	2.55***	-0.142	2.22***
	(22.4)	(12.2)	(13.1)	(24.7)	(14.9)	(-0.629)	(11.7)
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	CCHS	CCHS	CCHS	CCHS	CCHS	CCHS
Observations	131553	29747	29747	29747	29747	29747	29747
R^2	0.139	0.073	0.078	0.059	0.072	0.163	0.099

See the footnotes to Table 1.

and location-specific characteristics or local climate are correlated with both weather and LS. In the previous estimations, we accounted for these variations by controlling for station-month of individuals. It is also possible to control for the climate variations by directly accounting for long-term climate variables associated with each respondent's location. Brereton et al. (2008), Barrington-Leigh (2009), and Feddersen et al. (2012) have included this type of model in their analysis.

The climate variables used in our specifications can be divided into three categories: those that are related to long-term annual, monthly, and daily averages for different stations. The climate variables in Feddersen et al. (2012) are only at the annual level. Accounting only for yearly averages might not properly reflect the actual climate in an area due to the climate variations throughout the year. Table 9 shows the results of different estimations. In all the specifications we also control for the location-specific covariates correlated with both climate and LS as well as seasonal variations by including dummy variables representing different province-months.[3]

In columns (1-8) we look at the effect of climate on LS in our panel data set both with and without individual fixed effects. Models in columns (1-2) contain only annual climate variables. The effect of the annual climate variables in the panel data could only be identified in the subsample of respondents who have changed their location from one cycle to another. So, the respondents with the same assigned station in all cycles are dropped. Moreover, for each respondent we only consider the consecutive cycles in which the assigned station has changed. This reduces the sample size to about one fifth of the original sample. In columns (3-4) monthly variables are added, while columns (5-6) contain annual and daily variables and columns (7-8) control for daily and monthly averages.

As can be seen in Table 9, there is no strong evidence for the impact of climate on LS. The yearly and daily average differences in maximum and minimum temperature are statistically significant in the estimations with and without individual fixed effects respectively. Estimating the climate effect on both panel and pooled sample, Feddersen et al. (2012) find that, while climate effect is not statistically significant in the estimation with panel data, it is found to affect LS in their pooled sample. It should be noted that, except for Feddersen et al. (2012), all the studies showing the impact of climate on LS use cross-sectional data (e.g. Brereton et al., 2008; Feddersen et al., 2012). On the other hand, as mentioned earlier, the set of climate variables in Feddersen et al. (2012) is very small and might not properly reflect climate conditions in different places. This problem, along with a rather small sample size of our panel data set, suggests that further panel analysis is needed to test for the direct effect of climate on individual LS.

[3] While the change in climate is negligible within the areas close to each monitoring station, climate variations exist within each province.Thus, in estimating the impact of climate we account for geographic fixed effects at province level instead of station level.

In the last two specifications, we estimate the effect of weather when there is a control for the long-term averages on the day of the interview. Thus, instead of controlling for station month fixed effects, we use a set of long term climate variables. The results of these estimations show that the rain coefficients are not statistically different from what was obtained in Table 4 with station-month fixed effects.

Table 9: Climate and life satisfaction

Year: $T_{mean}(^{\circ}C)$	-0.0011	-0.0103	-0.0005	-0.0048	0.0001	-0.0066				
	(0.102)	(-0.755)	(-0.174)	(-0.553)	(0.029)	(-0.708)				
Year: $T_{max}\_T_{min}(^{\circ}C)$	0.0161	-0.0280	0.0007	-0.0357**	-0.0117	-0.0394**				
	(0.851)	(-1.128)	(0.084)	(-2.016)	(-1.528)	(-2.008)				
Year: Days sunny	-0.0004	0.0010	0.0002	0.0002	0.0003	0.0003				
	(-0.378)	(-0.723)	(0.513)	(0.311)	(0.676)	(0.163)				
Month: T_{mean}			-0.0074 *	-0.0018			-0.0036	-0.0007		
			(-1.857)	(-0.341)			(-0.811)	(-0.106)		
Month: days sun			-0.0008	0.0067			-0.0098	0.0024		
			(-0.129)	(0.901)			(-1.595)	(0.276)		
Month: days snow			-0.0038	-0.0019			-0.0023	-0.0020		
			(-1.468)	(-0.881)			(-0.876)	(-0.871)		
Month: days rain			0.0065	0.0050			0.0071	0.0079		
			(1.008)	(1.035)			(0.847)	(1.432)		
log (HH income)	0.1673***	0.0902*	0.2012***	0.0864***	0.2055***	0.0837***	0.2039***	0.0804***	0.2183***	0.0946***
	(4.717)	(1.671)	(13.946)	(3.928)	(14.999)	(3.949)	(14.886)	(3.775)	(15.584)	(3.795)
Day: T_{mean}					-0.0003	0.0021	-0.0007	0.0004	0.0019	0.0010
					(-0.113)	(0.583)	(-0.204)	(0.084)	(0.555)	(0.207)
Day: T_{max}-T_{min}					0.0180**	0.0040	0.0167**	0.0001	0.0158*	0.0096
					(2.108)	(0.372)	(2.029)	(0.006)	(1.707)	(0.675)
Day: precipitation					0.0019	-0.0001	-0.0003	-0.0015	0.0006	0.0010
					(1.344)	(-0.064)	(-0.182)	(-0.689)	(0.356)	(0.448)
T_{mean}									0.0010	0.0009
									(0.464)	(0.421)
$T_{max}\_T_{min}$									-0.0043	-0.0049*
									(-1.333)	(-1.325)
rain (mm)									-0.0019	-0.0014
									(-1.311)	(-1.018)
snow (cm)									0.0074*	0.0043
									(1.814)	(0.722)
cloud									0.0066	-0.0068
									(0.333)	(-0.277)
cloud (7 days)									0.0385	0.0006
									(1.243)	(0.014)
Constant	2.91***	4.01***	2.18***	3.92***	1.95***	4.112***	2.25***	3.93***	1.99***	3.91***
	(6.70)	(6.32)	(12.8)	(8.73)	(8.35)	(6.93)	(9.73)	(9.95)	(8.33)	(9.06)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS
Individual fixed effects	N	Y	N	Y	N	Y	N	Y	N	Y
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Prov.-month fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	NPHS	NPHS	NPHS	NPHS	NPHS	NPHS	NPHS	NPHS	NPHS	NPHS
Observations	2466	2466	15327	15327	14641	14641	14638	14638	10648	10648
R^2	0.095	0.719	0.0772	0.658	0.075	0.656	0.075	0.655	0.080	0.686

See the footnotes to Table 1

In columns 1 and 2 we dropped the individuals who have been in the same station in different cycles, since only the yearly climate variables

4 Conclusion

The use of subjective well-being (SWB) measures, chief among them life satisfaction (LS), has been increasingly accepted by social scientists to complement objectively quantifiable outcomes such as income and some health measures. An important reason for the extensive use of subjective measures is that several causes of skepticism in this area have been addressed. Nevertheless, as new, extensive data sets arise, the reliability of these measures and the source of different biases in reporting them can be more precisely addressed.

Individuals' moods at the time of reporting LS scores usually has no impact on the average reported LS since mood variations are assumed not to be correlated across individuals. However, if these variations are caused by a factor such as the transient component of weather, with similar and correlated impact across individuals, the variations might result in a type of psychological bias in reporting LS. Evidently, recognizing the source of such impacts will result in a more reliable assessment of the effect of LS determinants. In this study we shed light on the impact of transient weather as a factor that affects survey-reported satisfaction with life by employing a stricter set of fixed effects than those used in past studies.

After controlling for local and seasonal climate, we find that the daily variations in rainfall have an impact on LS. This impact is statistically significant in our cross-sectional data set (CCHS), but not statistically significant in the panel data set (NPHS). Our results support previous literature on the relation between weather and LS. This effect is robust to a number of alternative approaches such as estimation with ordered probit model. Although statistically significant, the marginal effect of the weather variables is smaller than many determinants of well-being. The effect of marginal variation in rainfall throughout the year is similar to the effect of 1% change in household annual income. While 1% of income may sound large in some contexts, it is relatively minor given that a number of non-pecuniary predictors of LS tend to have large income-equivalent effects. We also show that not accounting for weather variables is not of great importance when estimating the effect of the recognized socioeconomic determinants of LS. However, to avoid omitted variable bias, weather variables must be included in models when estimating the impact of a factor, such as air pollution, that is correlated with both weather and LS.

The results of estimating the model separately for males and females as well as for different health groups show that females and individuals with health problems are more affected by weather variations. When individual fixed effects are controlled for in panel data, the effect of none of the weather variables is found to be significantly different from zero.

We then investigate a hypothesis recognizing the cognitive complexity of assessing general life satisfaction as the main cause of biases such as weather bias. As a support to this hypothesis, we find no statistically significant impact of weather on domain-specific measures of LS, which are assumed to be evaluated with less cognitive complexity.

Estimation of the impact of long term climate variables using the NPHS sample shows that there is no strong evidence for the impact of climate on LS. This is in contrast with the results of the previous studies that show the impact of climate on LS in cross-sectional date sets, but not in panel data sets. However, further analysis on large panel data sets which include a larger subsample of relocated respondents can help to investigate the impact of climate to LS. As a practical implementation this study suggests that, in evaluating the impact on LS, weather variables should be considered if the variable of interest is correlated with transient weather conditions. For example, in evaluating the impact of air pollution on LS, omitting weather variables that are correlated with pollution will result in biased coefficients. We have also shown that weather bias is mainly associated with the estimation of cross-sectional data. Considering panel data to complement the widely used repeated cross-sectional data sets such as the Gallup World Poll can address weather bias to some extent.

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A Appendix

Table A.1: Weather and life satisfaction, without geographic controls

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS	(10) LS	(11) LS	(12) LS
cloud	0.0002	0.0077	0.026**									
	(0.05)	(0.59)	(2.3)									
$T_{mean}(^{\circ}C)$				-0.0002	-0.0001	-0.0010						
				(-0.88)	(-0.13)	(-1.2)						
T_{max}-$T_{min}(^{\circ}C)$							0.0003	-0.0021	-0.0029*			
							(0.49)	(-1.1)	(-1.7)			
snow (cm)										0.0005	0.0029	0.0072**
										(0.34)	(0.80)	(2.0)
log (HH income)	0.158***	0.0876***	0.201***	0.160***	0.0922***	0.184***	0.160***	0.0921***	0.184***	0.160***	0.0882***	0.197***
	(30.9)	(3.50)	(15.9)	(32.5)	(4.31)	(15.2)	(32.5)	(4.31)	(15.1)	(28.9)	(3.77)	(14.9)
Constant	3.00***	3.36***	2.74***	3.04***	3.20***	2.88***	3.03***	3.23***	2.92***	2.99***	3.34***	2.73***
	(45.0)	(11.5)	(16.8)	(47.3)	(12.9)	(18.5)	(46.9)	(12.8)	(18.6)	(41.0)	(12.3)	(16.1)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	166949	10253	14746	175086	13940	15619	175086	13940	15619	142591	11698	13093
R^2	0.071	0.671	0.076	0.073	0.667	0.068	0.073	0.667	0.068	0.073	0.680	0.073

See the footnotes to Table 1.

Table A.4: Summary of variables (CCHS)

Variables	Obs.	Mean	Std. Dev.
Satisfaction-Life	206859	4.27	0.70
Satisfaction-health	206859	3.73	0.97
Satisfaction-job	47843	4.14	0.867
Satisfaction-financial situation	47843	3.69	1.05
Satisfaction-friends	47843	4.35	0.70
Satisfaction-housing	47843	4.27	0.82
Satisfaction-neighbors	47843	4.22	0.82

Variables	Obs.	Mean	Std. Dev.
Household income ($)	47843	82714	85337
Health Index	70420	0.89	0.17
Age	206859	42.91	17.76
Female (dummy)	206859	0.50	0.50
Male (dummy)	206859	0.50	0.50
Married (dummy)	206859	0.49	0.50
Common-law (dummy)	206859	0.11	0.31
Widowed (dummy)	206859	0.04	0.19
Separated (dummy)	206859	0.03	0.16
Divorced (dummy)	206859	0.05	0.22
Single (dummy)	206859	0.28	0.45
At work last week (dummy)	206859	0.61	0.49
Absent last week (dummy)	206859	0.05	0.22
No job last week (dummy)	206859	0.23	0.42
Unable permanently to work (dummy)	206859	0.02	0.14
Less than secondary (dummy)	206859	0.05	0.23
Secondary graduate(dummy)	206859	0.09	0.29
Some post secondary (dummy)	206859	0.05	0.22
Post secondary graduate (dummy)	206859	0.75	0.43
Mean Temperature ($^{\circ}C$)	173635	7.22	10.74
Temperature difference ($^{\circ}C$)	173635	9.78	4.32
Rain (mm)	140903	2.25	5.97
Snow (cm)	141662	0.47	2.11
Cloud cover	165807	1.10	0.69
Cloud cover (7 days)	181485	1.18	0.47
Year: $\mathrm{T}_{mean}(^{\circ}C)$	206854	6.45	3.08
Year: $\mathrm{T}_{max}\_\mathrm{T}_{min}(^{\circ}C)$	208800	9.68	1.50
Year: days sun	194456	295.15	28.96
Month: $\mathrm{T}_{mean}(^{\circ}C)$	206846	6.63	9.95
Month: days sun	193738	25.09	3.86
Month: days snow	206832	5.69	9.47
Month: days precipitation	206846	4.72	2.33
Day: $\mathrm{T}_{mean}(^{\circ}C)$	191575	6.39	9.94
Day: T_{max}-$\mathrm{T}_{min}(^{\circ}C)$	191575	9.77	2.29

Table A.2: Weather and life satisfaction, allowing for local fixed effects

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS	(10) LS	(11) LS	(12) LS
cloud	0.0020	0.0049	0.025*									
	(0.35)	(0.50)	(1.8)									
$T_{mean}(^{\circ}C)$				0.0002	-0.0004	-0.0005						
				(0.77)	(-0.47)	(-0.51)						
T_{max}-$T_{min}(^{\circ}C)$							-0.0003	-0.0021	-0.0044**			
							(-0.37)	(-1.2)	(-2.1)			
snow (cm)										-0.0012	0.0028	0.0046
										(-0.71)	(0.74)	(0.96)
log (HH income)	0.158***	0.0816***	0.215***	0.166***	0.0910***	0.200***	0.166***	0.0927***	0.199***	0.167***	0.0884***	0.212***
	(19.4)	(3.37)	(15.3)	(20.6)	(3.98)	(13.3)	(20.6)	(4.15)	(13.1)	(17.5)	(3.44)	(13.9)
Constant	3.00***	3.30***	2.71***	2.99***	3.05***	2.82***	3.00***	3.27***	2.8663***	2.95***	3.4188***	2.67***
	(34.7)	(12.6)	(16.1)	(39.6)	(12.0)	(16.5)	(39.3)	(12.3)	(16.6)	(34.4)	(11.1)	(15.6)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	166949	13198	14746	175086	13940	15619	175086	13940	15619	142591	11698	13093
R^2	0.072	0.682	0.099	0.080	0.675	0.090	0.080	0.668	0.091	0.080	0.681	0.093

See the footnotes to Table 1.

Table A.3: Weather and life satisfaction, allowing for seasonal and local fixed effects

VARIABLES	(1) LS	(2) LS	(3) LS	(4) LS	(5) LS	(6) LS	(7) LS	(8) LS	(9) LS	(10) LS	(11) LS	(12) LS
cloud	-0.0018	0.018*	0.032***									
	(-0.39)	(1.6)	(2.8)									
$T_{mean}(^{\circ}C)$				-0.0003	-0.0004	0.0009						
				(-0.46)	(-0.25)	(0.48)						
T_{max}-$T_{min}(^{\circ}C)$							-0.0005	-0.0011	-0.0042*			
							(-0.53)	(-0.67)	(-1.9)			
snow (cm)										-0.0010	0.0019	0.0036
										(-0.65)	(0.41)	(0.76)
log (HH income)	0.164***	0.0667***	0.216***	0.166***	0.0779***	0.198***	0.166***	0.0781***	0.197***	0.166***	0.0731***	0.214***
	(29.8)	(2.97)	(13.4)	(32.3)	(3.48)	(13.0)	(32.3)	(3.5)	(13.0)	(28.0)	(2.99)	(13.1)
Constant	2.98***	3.62***	2.6562***	3.00***	3.30***	2.77***	3.01***	3.31***	2.80***	2.95***	3.63***	2.62***
	(42.2)	(12.3)	(11.7)	(45.0)	(11.1)	(13.3)	(44.4)	(11.)	(13.5)	(38.7)	(11.1)	(11.3)
Individual fixed effects	N	Y	N	N	Y	N	N	Y	N	N	Y	N
Socioeconomic covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station-month fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Survey	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS	CCHS	NPHS	NPHS
Observations	165807	11785	13268	173635	12177	13790	173635	12177	13790	141662	10535	11888
R^2	0.092	0.703	0.131	0.091	0.704	0.122	0.091	0.704	0.123	0.089	0.705	0.123

See the footnotes to Table 1.

Table A.5: Summary of variables (NPHS)

Variables	Obs.	Mean	Std. Dev.
Satisfaction-Life	15880	4.24	0.71
Satisfaction-health	15880	3.69	0.90
Household income ($)	15880	88270	67393
Health Index	15880	1.05	1.20
Age	15880	46.08	16.84
Female (dummy)	15880	0.50	0.50
Male (dummy)	15880	0.50	0.50
Married (dummy)	15880	0.51	0.50
Common-law (dummy)	15880	0.11	0.31
Widowed (dummy)	15880	0.05	0.21
Separated (dummy)	15880	0.03	0.17
Divorced (dummy)	15880	0.06	0.24
Single (dummy)	15880	0.25	0.43
At work last week (dummy)	15880	0.66	0.47
Absent last week (dummy)	15880	0.06	0.24
No job last week (dummy)	15880	0.21	0.41
Unable permanently to work (dummy)	15880	0.01	0.11
Less than secondary (dummy)	15880	0.12	0.32
Secondary graduate(dummy)	15880	0.12	0.32
Some post secondary (dummy)	15880	0.27	0.44
Post secondary graduate (dummy)	15880	0.50	0.50
Mean Temperature ($^{\circ}C$)	13790	8.21	11.44
Temperature difference ($^{\circ}C$)	13790	9.89	4.18
Rain (mm)	11835	2.33	6.19
Snow (cm)	11888	0.41	1.90
Cloud cover	13268	1.08	0.68
Cloud cover (7 days)	14321	1.16	0.46
Year: $\mathrm{T}_{mean}(^{\circ}C)$	15880	6.43	2.93
Year: $\mathrm{T}_{max}\_\mathrm{T}_{min}(^{\circ}C)$	17950	9.81	1.50
Year: days sun	15424	296.04	26.71
Month: T_{mean} ($^{\circ}C$)	15877	7.90	10.70
Month: days sun	15353	25.50	3.79
Month: days snow	15877	5.45	9.87
Month: days precipitation	15877	4.67	2.16

Variables	Obs.	Mean	Std. Dev.
Day: $T_{mean}(^{\circ}C)$	16926	7.34	10.80
Day: T_{max}-$T_{min}(^{\circ}C)$	16926	10.03	2.19