Evaluating the short-term cost of low-level local air pollution: a life satisfaction approach

Christopher Barrington-Leigh*
Fatemeh Behzadnejad

Dec 2015
Published in 2016 as DOI://10.1007/s10018-016-0152-7

Abstract

To estimate the impact of air pollution on well-being, we combine a set of repeated cross-sectional surveys of individuals with high resolution pollution and weather data. The respondents' level of life satisfaction is modeled as a function of their socio-economic characteristics and income as well as the weather and air pollution on the day of the survey interview. In order to overcome endogeneity problems, we include a set of high-resolution geographic fixed effects. Our analysis suggests that even after controlling for seasonal and local fixed effects, higher air pollution significantly reduces life satisfaction. The adverse effect of transient increases in air pollution is greater on individuals with poor health status. Estimating the average compensating differential between income and air pollution shows that the value of improving air quality by one-half standard deviation throughout the year is about 4.4% of the average annual income of Canadians.

KEYWORDS: SUBJECTIVE WELL-BEING, LIFE SATISFACTION, ENVIRONMENTAL ECONOMICS, ENVIRONMENT, AIR POLLUTION, PUBLIC GOODS, VALUATION

*To whom correspondence should be addressed at: McGill University, 1130 Pine Ave West, Montreal, H3A 1A3, Canada. The analysis presented in this paper was conducted at the McGill-Concordia Laboratory of the Quebec Inter-University Centre for Social Statistics which is part of the Canadian Research Data Centre Network (CRDCN), and funded by SSHRC, the CIHR, the CFI, Statistics Canada and the partner universities. The views expressed in this paper do not necessarily represent the CRDCN's or that of its partners'. Barrington-Leigh was supported by funding from the Social Science and Humanities Research Council of Canada and the Fonds Société et Culture de Québec.

Contents

List of Tables

1 Introduction

Preferences for different goods are commonly inferred from individuals' behavior in the market. For public goods with no market, such as air quality, it is not possible to follow this approach directly, since people usually have no opportunity to declare their real valuation or demand for public goods. To overcome this problem and capture the value of public goods, economists have used two main approaches. In the first approach, known as the stated preference approach, individuals are asked directly about the value to them of a public good in a hypothetical market. In the second approach, or the revealed preference approach, the demand for a public good is derived from preferences revealed in the markets for a substitute or a complement private goods.

The contingent valuation method, which is an example of the stated preference approach, is based on surveys that directly ask respondents about their valuations of a public good or their willingness to pay for it. Some scholars claim that the results of such surveys are not reliable due to various biases, such as respondents' tendency to give strategic responses. Another source of bias is the embedding effect, in which the scale or the scope of public goods is ignored in the process of valuation (Kahneman and Knetsch, 1992; Diamond and Hausman, 1994).

The hedonic price method, as a well-known example of the revealed preference approach, is based on the reflection of amenity value in the price of properties. This method assumes equilibrium in the housing market, complete information, rapidly adjusting prices, and zero moving costs. In this case, the ability of individuals to relocate eliminates the net benefit of living in any location.

Both hedonic pricing and contingent valuation methods are founded on the concept of utility as is usually perceived in conventional modern economic theory, in which preference is understood in terms of individuals' choices. However, in its original interpretation by some early economic philosophers such as Bentham and John Stuart Mill, utility is considered as a measure of pleasure or pain that individuals experience at any moment. Over the last two decades, a developing empirical stream in economics has revived this approach to utility as hedonic experience (experienced utility) rather than as a representation of preferences (decision utility). During this period, there has been an increasing interest in using subjectively measured well-being to investigate both macro and micro oriented subjects, in particular through large empirical analyses of the determinants of well-being in different countries (see Frey and Stutzer, 2002; Di Tella and MacCulloch, 2006, for surveys of economic studies). At the same time, the set of methods relying on objective outcomes has also become richer and more controlled. Zivin and Neidell (2013) review these developments, which include the identification of outcomes such as cognitive performance, behaviour, and specific health outcomes which can all be influenced by pollution levels.

Subjective well-being (SWB) data have also provided economists with a novel approach for the valuation of public goods. In recent years, the life satisfaction approach (LSA) has been introduced as a new method for non-market valuation of public goods. In essence, in this method life satisfaction (LS) is used as an empirical measure of individuals' welfare. Welfare is assumed to be a function of socioeconomic characteristics, environmental factors, and other covariates. If such a function is estimated, one can use the coefficient of an amenity or a public good to obtain the effect of that amenity on the welfare of individuals conditional on the other determinants of welfare. Additionally, the marginal effect of the amenity and income on LS can be used to estimate the marginal willingness to pay (MWP) or the compensating differential to keep the same level of welfare after a change in the amount of the available public good or amenity. Thus, MWP indicates the utility-constant tradeoff between a public good and income for an incremental change in the amount of that public good.

1.1 Subjective well-being and life satisfaction

It is necessary to explain further the two terms subjective well-being (SWB) and life satisfaction (LS). SWB refers to how people experience the quality of their life and includes both emotional reactions and cognitive judgments (Diener, 1984). The emotional reactions, moods, and feelings a person has are referred to as affect. Life satisfaction (LS), on the other hand, refers to the cognitive judgments about one's life as a whole and relates to what a person considers a good life to be. This measure is cognitively derived by a comparison of life circumstances with one's standards (Pavot and Diener, 1993), yet is informed by how good life simply "feels", and so offers a blend of cognitive judgments and affective states (Frey et al., 2010).

Life satisfaction and affect are measured separately and independently. Life satisfaction is usually derived from the responses of a single question asking how satisfied a person is with his life as a whole. Affect balance is measured using more complicated methods such as Experience Sampling Method (ESM)[1]. These two dimensions of SWB can be seen to encompass a range of philosophical interpretations of well-being. If individuals' welfare is considered to be represented by moment-to-moment affect, then the affect-related measures of SWB will be a better indicator of welfare. On the other hand, for those people who think of welfare as a "positive, persistent attitude towards both particular experiences and life experience more generally that a person feels upon repeated reflections" (Kelman, 2005), a general LS will be a more appropriate measure of welfare.

From the economic point of view, the subjectively experienced level of well-being is close to the idea of classical economists such as Bentham, who defined utility as a hedonic quality of experience that can be measured. We later discuss different utility concepts which provide different bases for the valuation of air quality.

[1] ESM asks participants to stop at certain times and make notes of their experience and report temporal things like feelings in that moment

1.2 The life satisfaction approach in the valuation of air quality

LS has been used to assess the valuation of individuals of a number of public goods and bads, such as climate conditions (Rehdanz and Maddison, 2008; Brereton et al., 2008), proximity to infrastructure (Brereton et al., 2008), and terrorism (Frey et al., 2009). It has also been used in a number of studies of air quality valuation. Assessing the value of air quality has been an interesting topic for researchers due to the significant impact of environmental conditions on well-being. Determining how crucial air quality is for an affected population may help in designing and implementing more beneficial air quality regulations, for instance when they conflict with greenhouse gas mitigation objectives[2] or with economic development goals. Due to the importance of air quality valuation, there are many studies that have investigated this issue using other approaches, such as the hedonic method (Chay and Greenstone, 2005; Rehdanz and Maddison, 2008) or the contingent valuation method (Carlsson and Johansson-Stenman, 2000).

We now focus on LSA studies of air quality valuation. A number of the early studies, such as Welsch (2002) and Welsch (2006), try to relate the average happiness in different countries to the countries' average level of pollution. In the later studies, such as Di Tella and MacCulloch (2008) and Luechinger (2010), although the dependent variable is individuals' LS, the pollution variable is still at the aggregated level of the country's average.

One problem with these studies is that there might be a considerable variation in air pollution within a country. The estimated effect of pollution on LS is biased if the real level of pollution to which the individuals were exposed is different from the average level. By using a finer spatial resolution, the pollution data for each respondent will be closer to the level of the pollution experienced by the individual. Levinson (2012), Luechinger (2009), and MacKerron and Mourato (2009) address this problem by using pollution data at postal code or county level. Moreover, most studies use repeated cross-section data sets in their estimations to account for the unobservable and time-invariant spatial characteristics correlated with pollution.

Di Tella and MacCulloch (2008) look at the Euro-Barometer survey series during a 23-year period from 1975 to 1997. They use a number of explanatory variables, such as crime, openness to trade, inflation, unemployment, and environmental degradation, in addition to income to examine the validity of the Easterlin paradox. In their study, an increase of sulfur dioxide (SO_2) level by one standard deviation has an effect that is similar to a 17% reduction in income. MacKerron and Mourato (2009) used their own web survey to measure the effect of nitrogen dioxide (NO_2) on LS for citizens of London. The marginal willingness to pay for 1 μg m^{-3} reduction in NO_2 concentration is $8k, which is a very large amount compared to similar studies. However, the validity of the results of this study is questionable given its small set of observations, selection bias issues in the web surveys, and the problem of omitted spatial variables in the non-repeated cross-section data set.

[2]For instance, encouraging diesel as a transportation fuel can represent a tradeoff between reducing greenhouse gas emission and reducing local particulate pollution.

As was mentioned earlier, using repeated cross-section and panel data can control, to some extent, for some of the unobserved variables correlated with pollution. However, the estimated coefficients may still be biased as a result of the correlation of local economic activities and pollution. In his two studies, Luechinger (2009; 2010) tries to account for this simultaneity problem by estimating the effect of pollution using an instrumental variable for pollution. The Luechinger (2010) study covers 12 European countries in the period 1974-1997, while Luechinger (2009) estimates the effect of SO_2 using a panel of individuals in 450 German counties during 1985-2003. In both studies, the inferred marginal willingness to pay is larger using the instrumental variable estimators compared to the conventional estimators. This suggests that better air quality has been accompanied by a number of factors with negative effects on LS.

In contrast to all the above-mentioned studies, in which the focus is on the effect of average annual pollution on LS, Levinson (2012) investigates the effect of daily variations of pollution. It is important to note that using the concentration of air pollutants on the interview day in estimations which control for geographic fixed effects will show only the effect on LS of temporal variations in pollution.

Frey et al. (2010) discuss the issue of spatial and temporal resolution of data. According to their study, while higher spatial resolution is always preferred, the choice of temporal resolution depends on the channel through which the pollution affects LS. If it is assumed that the effect on LS is through long-term problems, such as health problems or material damages, then average measures of air quality such as annual concentrations could be used. Conversely, as mentioned by Frey et al. (2010), if pollution affects the well-being of individuals because of aesthetic effects, such as reduced visibility or through acute health problems rather than chronic ones, then a higher temporal resolution is more appropriate.

In his study, Levinson (2012) finds a significant effect from daily variation of particulate matter (PM10) on LS using the US GSS data over 21 years. The implicit marginal willingness to pay to decrease daily pollution by 1 μg m^{-3} throughout the year is \$890.

Like Levinson (2012), we use a combination of short time scale variation and local geographic fixed effects in order to overcome major identification problems. Two primary sources of endogeneity when observing a correlation between life satisfaction and long-term pollution levels are that people may sort themselves geographically as a result of preferences over air quality, and that industry locates itself taking into account existing amenities. For instance, if relatively pollution-averse people are likely to move away from polluted areas or if relatively affluent, happy, and mobile people are likely to live in less polluted areas, then the estimated relationship between pollution and life satisfaction may be biased downwards or upwards, respectively. Similarly, larger, more polluting industrial facilities may be more likely to locate themselves in areas with lower land prices. These less desirable locations may have other preexisting disamenities, or lower economic opportunities, which result in lower satisfaction. In general, environmental and other amenities are often bundled, making it difficult to isolate the effects of one. For example, Depro et al. (2015) find measurable evidence of residential sorting driven by environmental amenities. However, by focusing on high-frequency (short-term) changes in pollution and by controlling for geographic fixed effects, we avoid these problems at the cost of measuring only the pollution effects which happen much faster than geographic sorting.

1.3 Overview

In the present study we first clarify some of the theoretical background underlying the use of the life satisfaction approach (LSA) in the valuation of public goods. The theoretical background and assumptions underlying the use of the LSA have not been adequately discussed in the other studies using this approach for the valuation of public goods. We first explain the relationship between subjective well-being measures and the concept of utility in the literature of modern economics. Next, we focus on life satisfaction as a measure of subjective well-being which depends on a number of stable personal and socioeconomic attributes as well as momentary factors. We then discuss how the variation in air pollution — the environmental good investigated in this study — can be related to income level of individuals in the LSA. We also discuss in detail the channels through which air quality affects well-being in short run and long run.

Our work is also the first study that investigates the relation between LS and air pollution in Canada. The spatial and temporal resolution of the environmental variables in our data set is higher than most of the studies on the welfare impact of pollution. The objectives of this paper are as follows: first, we show that after accounting for individuals' socioeconomic characteristics as well as geographic and temporal fixed effects, the day-to-day variation of SO_2 concentration has a significant effect on LS. This result is robust across a variety of empirical specifications. We also find that individuals' LS is not related in sensible ways to the daily variation of carbon monoxide (CO), nitrogen dioxide (NO_2), or fine particulate matters ($PM_{2.5}$). In addition, our analysis estimates the extent to which the effect of air pollution differs for respondents with various health conditions. We also test whether domain-specific satisfaction measures, which are obtained through less cognitively demanding questions, are affected by air pollution.

In our subsequent analysis, the income and the pollution coefficients are used to obtain the implicit marginal willingness to pay for an incremental improvement in air quality. The main result of this part is that the effect of pollution on happiness implies a marginal willingness to pay for SO_2 pollution reduction that is comparable to the MWP obtained in other LS studies on the effect of this pollutant. More specifically, we infer that Canadians would be willing to pay \$890 per year, which is about 1.1% of their annual income, to reduce the concentration of SO_2 by 1 μg m^{-3} throughout the year.

Average SO_2 pollution in Canada is low compared to the average levels in the two other studies using the LSA approach to estimate the impact of SO_2 (Luechinger, 2009, 2010). However, the compensating differential ratio is approximately the same in all studies. This implies a marginal effect of SO_2 on welfare which is similar at all pollution levels. On the other hand, the adverse impacts of air pollutants, such as SO_2, might increase more than proportionally in higher concentrations, suggesting a non-linear impact of air pollution on welfare. In order to test whether the welfare impact of SO_2 is more crucial at higher levels, we further examine a number of non-linear specifications.

The average level of many pollutants in Canada has decreased due to the implementation of different regulations in the last three decades. For SO_2, most provinces met the determined caps sometimes even earlier than the proposed deadline for abatement (CCME, 2011, pg. 21-33). Yet, many Canadians are affected by high SO_2 emissions, mostly in industrial regions as reported by air pollution monitoring stations. On the other hand, while the Canadian thresholds for some of the major pollutants are similar to those of WHO, the one-day threshold for SO_2 concentration in Canada is by far greater than the WHO suggested level. In the final section, we show that this difference between Canada and the WHO thresholds for SO_2 decreases individuals' well-being to a great extent in the polluted areas.

We proceed in Section 2 by further explaining the use of life satisfaction data in the valuation of public goods. We then discuss how the variation in air pollution can be related to income level of individuals in the LSA. This depends to a great extent on what life satisfaction captures as a measure of individuals' well-being. Central to this part is clarifying that LS is a measure of flow utility which depends on a number of stable personal and socioeconomic attributes as well as momentary factors. We also investigate the channels through which air quality affects well-being in the short run and long run. We continue with the explanation of the data sets and our empirical analysis in Section 3. Section 4 includes the results and discussion of different estimations. In Section 5, we briefly look at some issues related to air pollution, and specifically SO_2 pollution, in Canada and discuss the implications of the results in Section 4 in order to obtain the costs of air pollution. Section 6 concludes.

2 The rationale behind using the life satisfaction approach for environmental goods valuation

In modern economics, utility is best defined as a set of preferences which explains an individual's choices; this concept is known as decision utility (Kahneman, 2000). However, in its earliest conception, introduced by Bentham (1789) and used by 19th-century economists, utility has been defined as a flow of pleasure and pain experienced by people at a given time. Each utility concept is associated with a different approach to public goods valuation. The conventional methods of hedonic pricing and contingent valuation are based on decision utility. The life satisfaction approach (LSA), on the other hand, focuses on experienced utility or hedonic experience associated with an outcome. The LSA is based on the estimation of the impact of a range of socioeconomic and environmental attributes of individuals on their LS, which is taken to be a measure of their experienced utility.

Most of the studies related to subjective well-being (SWB) in economics have used representative and large-scale sampling of LS evaluations. Why is LS an appropriate SWB measure for the purpose of valuation? Central to this is that LS is a relatively stable measure of experienced utility that can be best depicted as a blend of cognitive assessment of life quality as a whole and responsiveness to transitory factors. Although LS is a measure of cognitive judgment about life quality, different studies show that such cognitive judgments are influenced by affective states (Frey et al., 2010; Schwarz and Strack, 1991). The reported score of LS for each individual depends on her relatively stable personal and social attributes as well as the characteristics of her environment, yet it is sensitive to momentary events and emotions. This type of experience-based and affect-contaminated cognition is close to the philosophical theory of Sumner (1996) on the nature of welfare[3]. In practice, LS reported on a scale between 0 and 10 is obtained from individuals' responses to a question asking how satisfied they are with their life in general.

According to Frey et al. (2010), for the measures of SWB to be valid for the valuation of public goods, the following six conditions should be satisfied. The measures of SWB should: (1) be valid measures of individual welfare; (2) be broad and inclusive; (3) refer to the respondents' present situation; (4) have small measurement errors; (5) be interpersonally comparable; and (6) be available at a sufficiently large scale. The study of Frey et al. (2010) consists of a detailed discussion along with references to the related studies to show that self-reported LS measures, mostly derived from the seemingly simple questions in surveys, satisfy these conditions.

Choosing a proper welfare measure to be applied in a method such as the LSA, especially when one estimates the impact from both stable and fluctuating variables, is very crucial. In fact, it is essential for the welfare measure to demonstrate stability and to maintain sensitivity to changes at the same time. LS is a suitable measure for this purpose as it provides a blend of more stable cognitive judgment and affective state. LS scores have substantial stability due to stable socioeconomic status, economic conditions, and social milieu, as well as stable personality traits. LS scores demonstrate high to moderate stability over time in panel data sets. The repeated-measure correlation (or over time for the same individual) is typically in the realm of 0.5 in a 5-years period (Fujita and Diener, 2005; Ehrhardt et al., 2000).

On the other hand, momentary factors such as mood and the priming of particular information can influence LS. Judgments of well-being, as measured by LS, depend not only on what one thinks about, but also on how one feels at the time of judgment. Experimental studies confirm the influence of minor events that might affect our mood, such as spending time in a pleasant rather than an unpleasant room or when one's favorite team wins a game, on reported LS (Schwarz et al., 1987). While various important and stable factors affecting well-being may not be varying quickly, the momentary experienced well-being,

[3] Sumner's theory of welfare is a subjective theory in which, for a state of affairs to make a person better off, it needs to enter her experience. Additionally, for the self-report of happiness to represent welfare, it is required that a subject's experience of (satisfying) states not be based on false beliefs and not be influenced by such things as coercion and exploitation (Sumner, 1996).

which depends in part on them, may vary in the short term due to changes in perception and currently experienced mood. As air quality variation affects individuals' momentary mood (Rotton, 1983; Bullinger, 1989), it can be one source of instability in reporting LS.

If LS reports can be used as an empirically valid measure of individuals' experienced utility, it is possible to directly find the impact of different variables affecting their welfare measured by this utility concept. The life satisfaction approach (LSA) to the valuation of environmental goods considers LS as a function of personal, socioeconomic and environmental characteristics related to the respondents. Since the LSA focuses on income and the public good to be valued (which is one of the social or environmental variables), all the other macro-level and individual-level determinants of well-being are considered as a vector variable (z_{it}) for simplicity. The respective relationship between LS, as a measure of experienced utility, and its determinants can be stated in the following form:

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

Individuals' well-being or experienced utility in terms of LS at the time of the interview (LS_{it}) depends on their income level (Y_{it}), the environmental good to be valued (x_{it}), and some other variables affecting LS such as individuals' personal and socioeconomic characteristics, as well as wider economic and local conditions (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 the sum of all covariates; each is weighted by a coefficient to be estimated. The OLS method then can be used to estimate the coefficients of this linear regression model.

The time index t indicates that the LSA identifies the impact from these factors on satisfaction at the time of the interview. The values of the variables such as age and employment status at the time of the interview can be assigned with no ambiguity. Regarding the variables such as economic or social conditions, most studies investigate the impact from the average levels recently experienced by a person on her current well-being and so use annual or monthly averages accordingly. However, as explained in the previous part, LS is also sensitive to temporal changes and so for volatile local conditions such as air quality one can estimate the impact from daily fluctuations on satisfaction. In the present study, similar to the study of Levinson (2012), we find the impact from daily variations of air pollution on LS while we control for the average pollution by accounting for location fixed effects. Before further explaining the LSA, it is necessary to clarify the time dimension of LS and its determinants in the LS function.

2.1 Temporal dimension of LS and its determinants

SWB measures represent individuals' welfare or experienced utility at the time of the interview. A reported score of LS reflects the experienced utility of a respondent at a given time and so measures a period or flow utility. The fact that SWB measures including LS imply an instantaneous utility at the time of the interview is clearly stated in the literature; see for example Frey and Stutzer (2002); Frey et al. (2010). A number of questionnaires such as the one for the recent cycles of the Canadian Community Health Survey (CCHS) ask "How satisfied are you with your life as a whole, right now?" to emphasize the fact that LS reflects a person's well-being as she experienced it at the interview time.

However, as LS questions usually ask people to evaluate their life as a whole, it is important not to confuse LS with the summation of utilities over a number of periods. In order to find out how time dimension is incorporated in reporting LS scores, it is essential to understand the cognitive judgment process that underlies the report of LS by individuals. When facing LS questions in surveys, it is often the case that respondents have not previously thought about the questions and judgments are developed at the time the questions are asked. In answering such questions, individuals rarely retrieve all the information that could potentially enter into the judgment. One central principle in reporting SWB scores is that individuals only use the most cognitively accessible information to respond to SWB questions (Schwarz and Strack, 1991). In the case of LS, empirical studies show that respondents' judgments depend on information such as their stable personal and socioeconomic attributes, the surrounding environment, and recent transitory life events. People report how favorable they experience their life to be at the time they answer the LS question where this experience is affected by a range of factors. Obviously, many of these covariates are fairly stable for a given individual over time.

Among all the determinants of well-being, the LSA focuses on the impact from income and the environmental good to be valuated—air quality in this paper—while controlling for the rest of the LS covariates. Regarding the channels through which air pollution can affect LS, both short-term and long-term effects are possible. Air pollution can have long-term consequences on LS mainly through adverse health effects and material damages. To capture such impacts, annual or monthly averages of pollution levels must be included in the regression. Most of the studies on well-being impacts of air pollution have obtained the effect of average pollution (Di Tella and MacCulloch, 2008; Luechinger, 2009, 2010).

On the other hand, pollution has short-term impacts on LS mainly by affecting individuals' mood, causing acute rather than chronic health problems, and aesthetic effects such as reduced visibility. In the current study, we are interested to see the impact from temporal changes in air pollution on LS by including pollution at daily level. We control for geographic fixed effects to capture the impact of variables that are correlated with both LS and air pollution. The size of the regions in our fixed effect analysis is such that it is less likely for the average annual pollution levels to have any significant variation within any region. Thus, the geographic fixed effects control for the average pollution experienced by the respondents.

The relation between income and SWB has been the subject of many empirical studies. In the microeconometric function of LS, income is always controlled for since it has a direct or indirect impact on report of LS scores. The income variable available in most surveys is the annual income. Given that for most people there is no considerable change in monthly income within a year, this variable can be a proper approximation of the recent income level experienced by a person.

2.2 Marginal willingness to pay for environmental goods in the LSA

The LSA provides a straightforward strategy for the valuation of public goods such as environmental goods. By measuring the marginal utility of the environmental good as well as marginal utility of income, one can obtain the trade-off ratio between income and environmental good. More precisely, if individuals' welfare is held constant, a change in the environmental good by one unit is valued by the amount of marginal rate of substitution between income and pollution. In the above function, this marginal rate of substitution or the implicit marginal willingness to pay (MWP) for the environmental good will be:

$$MWP = -dY_{it}/dx_{it} = (\frac{\partial f/\partial Y_{it}}{\partial f/\partial x_{it}})$$

This MWP is calculated using the coefficients of income and air pollution in the estimated regression of LS on its determinants. As reviewed in the introduction, this method has been used in different studies for public goods valuation. Frey et al. (2010) summarize the results of different studies applying this approach to the valuation of air quality.

As LS reflects the steady flow of instantaneous experienced utility from enduring conditions such as income—one rather stable individual characteristic—as well as daily pollution, it is possible to obtain the implicit willingness to pay for air quality improvement from the estimated model in the LSA. It is worth mentioning that, in our regression specification in which LS is a function of pollution and log income, the MWP is derived as a function of income and pollution coefficients as well as the amount of income. In this model, there is no change in the estimated coefficients if the income variable is chosen at either annual or daily (approximated by 1/365 of annual income) level due to the logarithmic form of the income variable.

However, to calculate the amount of MWP to reduce air pollution by one unit at the day of the interview, we need to use average daily income as it is reasonable that individuals trade-off the daily income to compensate for the pollution at the interview date. If the annual average income is used instead, the obtained MWP shows the willingness of individuals to improve air quality by one unit throughout the year based on the trade-off ratio at the interview date. This annual MWP will simply be 365 times the daily MWP.

3 Data and Methodology

The three main data sets used in this study are the Canadian Community Health Survey (CCHS), weather data, and air quality data from Environment Canada. The CCHS collects cross-sectional information on healthcare 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 an annual basis. Our analysis relies on the six recent cycles of 2005 to 2011; there was no survey in 2006. The LS question was not asked in the surveys prior to this period. The question relevant to LS in the CCHS is the following: How satisfied are you with your life in general? The respondent is asked to choose one of the five levels (or eleven levels in the last three cycles) of satisfaction ranging from very satisfied to very dissatisfied.

The CCHS sampling strategy is geographically stratified at the level of health regions, which vary in size across Canada. However they typically consist of multiple Census Subdivisions (CSDs). There are 5253 CSDs across Canada, out of which 40% have population below 1000. Our sample of respondents, which is restricted based on the proximity to monitoring stations, includes 225 CSDs with an average population of 246 in each. In our models, we use these CSDs to control for geographic fixed effects, and as clusters in the error structure.

Daily and hourly weather data are available online from the Environment Canada data server. Environment Canada collects weather data from about 1200 stations throughout the country. Daily information on temperature and precipitation is available at most of these stations. Air quality data are collected by the National Air Pollution Surveillance Program (NAPS) which monitors the quality of ambient air in different regions of Canada. We use daily average concentration data, matched to the day of interview for each respondent, for a number of pollutants; these data are available from the Environment Canada website's air pollution section. The set of pollutants being monitored differs somewhat from station to station.

The CCHS, air pollution, and weather data sets are combined to obtain the necessary covariates for each respondent. Importantly for the purpose of this study, both the interview date and the postal code of the respondents are available in the non-public version of the CCHS. Having the geographic coordinates as well as the date of the interview, it is possible to find the weather and air quality information of the nearest station to each respondent on the interview day. In our data set, the weather and pollution information is collected at the nearest station(s) within a maximum distance from each respondent. The maximum distance is 30 kilometers for the weather data and 5 kilometers for the pollution data. Table 1 contains the statistics regarding the air pollutants to which the respondents were exposed as well as the number of days when the pollution level was above the WHO guideline thresholds. We also include the hours or the days with pollution above the thresholds for all the NAPS stations throughout Canada from Wood (2012). Different provincial thresholds used in Wood (2012) are higher than the suggested levels in the WHO guideline (World Health Organization, 2006). Table 9 provides the descriptive statistics for the variables used in different estimations in this study

It should be noted that in recent years the availability of panel data sets that include LS has made it possible for researchers to control for individual heterogeneity. Accounting for individual fixed effects results in more reliable evidence as individual traits are correlated with both LS and the determinants of well-being. For the purpose of the present study, however, the subset of the panel data set available to us (The National Population Health

Survey (NPHS)) for which both pollution and weather information can be assigned was small. Another source of hereogenity related to the impact of air pollution is difference in individuals' sensitivity to air pollution (Luechinger, 2009). If similar air pollution level affects individuals differently, in a sorting equilibrium the least sensitive individual will live in the most polluted area and vice versa. This type of heterogeneity has an impact on the estimates of air pollution coefficient as well as the MWP. However, according to the Chay and Greenstone (2005) study, which accounts for this type of sorting in a hedonic framework, the impact of this heterogeneity on the estimated WTP at aggregate levels such as counties (or subdivisions considered in our study) is negligible.

Table 1: One-day level of the major air pollutants and the number of days above the thresholds for the CCHS respondents and for Canada

				CCHS (2005-2011)		Canada[a] (2000-2008)		
Air pollutant	Mean	standard deviation	Max. (daily)	Exceedance of WHO thresholds	Exceedance of Canada thresholds	Exceedance of Canada thresholds	Canada[b] thresholds	WHO thresholds
CO (ppm)	0.22	0.22	3	0 days	0 days	0 hrs.	12(1 hr.)	10(8 hrs.)
NO_2(ppb)	13.5	8.23	69	476 days	85 days	230 hrs.	106(1 hr.)	50[c]
$PM_{2.5}$(ppm)	7.4	6.44	175	1973 days	1973 days	3560 hrs.	25(24 hrs.)	25(24 hrs.)
SO_2(ppb)	1.69	2.93	127	1615 days	61 days	1169 days	44(24 hrs.)	8(24 hrs.)

[a]Data in this column are from Wood (2012)
[b]These are the limits used in Wood (2012) . They are respectively related to British Columbia 1-hour objective, 1-hour WHO guideline, British Columbia 24-hrs. objective and Alberta 24 hrs. objective.
[c]There is no 24-hours threshold in the WHO guideline. The hourly and annual thresholds are 106 ppb and 21 ppb.

In the LSA, the relation between LS and its determinants is estimated by the following equation:

$$\mathrm{LS}_{it} = \alpha \log Y_{it} + \beta \mathrm{pol}_{it} + X_{it}\gamma + \lambda_{it} + y_t + m_t + \varepsilon_{it} \tag{1}$$

In this equation, LS_{it} is the LS of individual i at time t. $\log Y_{it}$ is the logarithm of household income at time t, which is approximated by $\frac{1}{365}$ of annual income. X_{it} is a vector of socioeconomic characteristics of individual i. pol_{it} is the pollution level at the nearest station to the individual i on the day of the interview. y_t represents a set of dummies for the year and thus accounts for the effect of the year-specific shocks. Similarly, m_t accounts for monthly seasonal fixed effects. Variable λ_{it} represents a set of dummies to control for the location of the respondents. The model error ε_{it} is assumed to include a term clustered at the geographic level of subdivisions, in addition to an idiosyncratic component.

To obtain the marginal rate of substitution between income and pollution, we apply the condition $dLS_{it} = 0$. Assuming no change in all the variables other than income and pollution, equation (1) gives

$$\frac{dY_{it}}{d\,\mathrm{pol}_{it}} = -\frac{\beta}{\alpha}Y_{it} \tag{2}$$

In other words, $-\frac{\beta}{\alpha}Y_{it}$ is the compensating differential (CD) that shows the additional income needed (by individual i) to compensate for the negative effects of a one-unit increase in air pollution on LS. Therefore, the satisfaction level will remain unchanged after a one-unit increase of pollution if the CD is added to the income. This marginal rate of substitution can also be interpreted as the marginal willingness to pay (MWP) of individual i for better air quality.

For the purposes of equation (1), we can calculate the MWP equally well as the change in one-day income (Y_{it}) to compensate (for) a one-day unit change in pollution level,[4] or as a change to annual income $365Y_{it}$ to compensate for a uniform unit pollution change throughout the year, or indeed as 365 units of pollution change spread in any fashion throughout the year. However, when we consider non-linear dosage effects of pollution exposure, below, it will make more sense with regard to high pollution levels to interpret the MWP as a one-day hypothetical payment for a one-day change in pollution.

4 Results

SO_2 as a major air pollutant in industrialized countries has been the subject of many studies on the impacts of air pollution. This gas is emitted in the combustion of sulfur-containing fossil fuels, for example in electricity generation power plants, petroleum refining, and motor vehicles. The most important negative effects of SO_2 include adverse health effects and formation of acid rain.

The major adverse impacts of SO_2 on health, such as increase of mortality, respiratory symptoms, and aggravation of existing cardiovascular diseases, arise in the relatively high concentration of this pollutant (Katsouyanni et al., 1997; Atkinson et al., 1999). In addition to the health effects, high concentrations of SO_2 reduce visibility and, together with NO_x, are the major causes of acid rain. Acid rain has adverse impacts on soil, fresh water, and forests and, can contribute to the corrosion of buildings and metals. The World Health Organization's air quality guideline for SO_2 in the latest version issued in 2006 limits the

[4]On the day of the interview, the respondents' SWB reflects their one-day income level, which we can take to be proxied by $\frac{1}{365}$ of their annual income, and the one-day pollution level which we measure. Because we include geographic dummies, the linear model reflects only the variation (changes) from the mean pollution level.

concentration of this pollutant to 20 μg m^{-3} (8 ppb) for the one-day average (World Health Organization, 2006).

The proposed guidelines by the WHO and Environment Canada are based on studies focusing on the major health effects of SO_2 that mostly happen at pollution levels above the threshold. However, a number of studies present some evidence for minor health problems caused by low emissions of this pollutant. Lower concentrations of SO_2 are associated with an excess of coughs, respiratory infections, and headaches (Partti-Pellinen et al., 1996; Szyszkowicz, 2008).

The average annual level of SO_2 in Canada has been about 2 ppb in recent years, but Canadians might be exposed to higher concentrations of this pollutant. According to Wood (2012), 6% to 50% of all the monitoring stations in Canada reported a number of days with a one-day average higher than 44 ppb (the 24-hour average in the Alberta Ambient Air Quality Objectives) in the period 2000 to 2008. The average one-day level of SO_2 in our data is 1.86 ppb, which is a relatively low concentration for this pollutant. However, individuals experience a range of SO_2 concentrations within each region. On any given day with an SO_2 level a little higher than the regional average, the possible channel for SO_2 having an influence on LS is through minor health problems affecting mood, the opportunity cost of any avoided activities, as well as through aesthetic value or beliefs which affect mood. On a day with a higher pollution level than the average, more important acute health problems, the worsening of chronic problems, and reduced visibility could affect individuals' LS.

Table 2 reports the different estimations of equation (1). The model estimated in column 1 of Table 2 contains only income and the one-day level of SO_2 concentration. The variables have the expected sign, but the coefficient of SO_2 is not statistically significant. In Column 2, the long-term monthly average of SO_2 in the nearest pollution station is added. Adding the monthly level of pollution increases the coefficient for the one-day SO_2 concentration; however, none of the daily and monthly pollution coefficients are statistically significant.

Column 3 omits the annual level of SO_2 and adds fixed effects for the locations of the respondents. The subdivision fixed effect controls for time-invariant heterogeneity among census subdivisions. In Canada, a census subdivision is a municipality or an area that is deemed to be equivalent to a municipality. Controlling for the subdivision fixed effect helps in isolating the effect of the one-day pollution from that of the locally specific variables correlated with pollution and affecting LS. We also cluster the standard errors at the level of subdivisions. After the inclusion of the subdivision fixed effect, the coefficient of the one-day pollution increases compared to column 1, but it is not statistically significant.

In column 4, we account for the demographic and the socioeconomic variables that are the most commonly used predictors of LS. These variables consist of age, age squared, sex, marital status, employment status in the week prior to the interview, and the educational level of the respondents. For each of these variables, a series of dummy variables categorizes the respondents into different groups. Confirming the results of other studies, women, married, more educated, and employed individuals are more satisfied with their life. Satisfaction with life decreases by age up to 50 and increases afterwards. The coefficient of the one-day SO_2 concentration is negative, but not statistically significant.

Finally, in column 5 we control for a number of daily weather variables. These include average temperature, the difference between maximum and minimum temperature, precipitation, and cloud cover on the day of the interview. Daily weather variables are shown to be correlated with LS (Barrington-Leigh, 2009; Feddersen et al., 2012)as well as pollution (Levinson, 2012). After controlling for the weather conditions on the day of the interview, the coefficient of the one-day SO_2 is statistically significant and also larger compared to the previous estimations.

The coefficient of air pollution suggests that an increase of one-day SO_2 level by 10 μg m^{-3} (equivalent to 3.88 ppb) decreases LS by 0.02, where satisfaction is measured on a scale of 0 to 5. The log income coefficient suggests that a 10% increase of household annual income will result in an increase of 0.017 in LS level. The coefficient of air pollution is small compared to those coefficients related to being permanently unable to work (-0.358) or separating from a partner (-0.0954). However, an increase of the one-day SO_2 concentration by one standard deviation throughout the year has an effect of a roughly similar magnitude to a 10% decrease in annual income.

To give a more economic sense of the air pollution value to the respondents, the average marginal rate of substitution between pollution and income, or the marginal willingness to pay for air quality improvement, is calculated. The average MWP is obtained by replacing the coefficients of pollution and the log of income as well as the average annual household income in equation (2). The values of MWP along with their standard errors are reported for the different specifications in all the tables. Focusing on the estimation in column 5, the MWP to reduce SO_2 pollution by 1 ppb is $1995.

In order to be able to compare the results with those of the previous studies, the MWP for a 1 μg m^{-3} reduction of SO_2 is calculated by dividing the above MWP by the relevant conversion factor.[5] So, an individual with a household income of $78k, which is the average income in our data set, is willing to pay $890 to reduce the SO_2 level by 1 μg m^{-3} throughout the year. The MWP to decrease SO_2 pollution by one standard deviation is $19 per day. The MWP for all the specifications are declared in the last row of each table.

The ratio of the MWP to reduce SO_2 by 1 μg m^{-3} throughout the year to total household income in our data set is about 1.1%. Frey et al. (2010) summarize the results of the studies that use the LSA to evaluate the MWP to reduce air pollution. There are two other studies with the same approach to investigating the impact of SO_2 on LS. The MWP obtained in these studies are about 1.1% of household income in Luechinger (2010) and 0.9% of household income in Luechinger (2009) in his most comprehensive models.

Table 2: The effect of pollution on LS

Dependent variable	LS	LS	LS	LS	LS

[5] For SO_2, 1 ppb is equivalent to 2.6 μg m^{-3}

SO_2 24 hrs. (ppb)	-0.0011 (-0.6)	-0.0024 (-1.18)	-0.0025 (-1.352)	-0.0028 (-1.438)	-0.0052* (-1.972)
$\overline{SO_2}$ by station and month (ppb)		0.0042 (1.048)			
ln (household income)	0.203*** (29.10)	0.203*** (29.67)	0.213*** (32.44)	0.173*** (21.89)	0.173*** (22.70)
female				0.049*** (6.23)	0.055*** (5.45)
Age				-0.027*** (-12.870)	-0.027*** (-9.822)
Age squared				0.00028*** (11.96)	0.00027*** (9.665)
Married				0.152*** (8.802)	0.143*** (6.879)
Common law				0.119*** (6.339)	0.101*** (4.120)
Widowed				0.024 (1.454)	0.035 (1.475)
Separated				-0.062** (-2.112)	-0.095** (-2.315)
Divorced				-0.036 (-1.489)	-0.003 (-0.097)
At work last week				0.100*** (3.809)	0.070** (2.171)
Absent from work last week				0.115*** (3.313)	0.165*** (3.780)
No job last week				0.069*** (2.977)	0.042 (1.392)
Permanently unable to work				-0.361*** (-8.121)	-0.358*** (-6.310)
Secondary graduate				0.060*** (2.954)	0.057* (1.816)
Some post secondary				0.091*** (3.946)	0.092*** (3.605)
Post secondary graduate				0.086*** (3.846)	0.102*** (3.479)
Weather Variables					
Mean temperature (°C)					-0.0004 (-0.302)
Temperature difference (°C)					0.0005 (0.212)
Rain (mm)					-0.0019* (-1.680)
Snow (cm)					-0.0035 (-0.905)
Cloud cover					0.0081 (0.444)
Constant	2.014*** (25.21)	2.014*** (26.31)	2.052*** (25.05)	2.733 (27.84)	2.733 (18.75)
MWP to reduce SO_2 by 1 μg m^{-3}	\$159(265)	\$330(319)	\$331(245)	\$457(319)	\$890(454)
Month fixed effect	N	N	Y	Y	Y
Year Fixed effect	N	N	Y	Y	Y

Subdivision fixed effect	N	N	Y	Y	Y
Clusters			225	225	124
R-squared	0.051	0.052	0.062	0.092	0.095
N	55324	55324	55324	55324	34587

*** statistically significant at 1%. ** statistically significant at 5%. * statistically significant at 10%.
t-statistic appears bellow each coefficient. Standard errors of MWP (in parentheses) are obtained by the delta method. Standard errors are clustered at the Subdivision level.
For the calculated MWP to be comparable with the amounts in similar studies, we report the MWP to reduce SO_2 by 1 μg m^{-3} throughout the year.

To check for the robustness of the results in Table 2, three alternative specifications are considered. The results are reported in Table 3. Column 1 in Table 3 uses income instead of the log of income. The second column is related to the regression on the log of SO_2 and the log of income.

Column 3 presents estimates of an ordered probit model. Since the LS scores are declared on an ordinal scale, ordered discrete choice models such as ordered probit have been used by researchers in LS studies. However, most of the studies find little difference between the results of the two methods (Ferrer-i Carbonell and Frijters, 2004). A number of studies on the relation of pollution and LS use both ordered probit and OLS, but only report the OLS coefficients because of the similarity of results from the two approaches Ferreira and Moro (2010); Luechinger (2010). In Levinson (2012), which includes estimates of both models, the difference between the MWP obtained by OLS and ordered probit is less than 1%.

All the specifications control for month, year, and subdivision fixed effects. They also account for all the demographic and socioeconomic variables considered in column 5 of Table 2. The estimated coefficients of income and pollution indicate that the variation of LS with income and SO_2 concentration is robust to different specifications.

The MWP in the first two columns are calculated differently from equation (2). For column 1 and 2, the (average) MWP to reduce pollution by 1 μg m^{-3} is equal to $\frac{\alpha}{\beta}$ and $\frac{\alpha}{\beta}\frac{\overline{Y}}{\overline{SO_2}}$ respectively, where $\overline{Y}$ is the respondents' average income. The MWP in column 1 is clearly higher than what has been obtained so far. However, the assumption of LS changing linearly with income leads to an income coefficient that is not statistically significant, and so the calculated MWP is not reliable.

Table 4 estimates the same specification as the one in column 5 of Table 2 for different air pollutants. The air pollutants in columns 1, 2, and 3 are carbon monoxide (CO), nitrogen dioxide (NO_2), and fine particulate matter ($PM_{2.5}$) respectively. The coefficients of the pollutants in columns 1 to 3 are not significant. Having no relation between pollution and LS is not a surprise for CO and NO_2. The levels of these pollutants in Canada are far below the acceptable level in the WHO guideline (World Health Organization, 2006). During the period 2000-2008, all the air quality stations in Canada recorded zero hours with CO concentration more than 12 ppm, which is the 1-hour allowed emission level for CO in Canada (Wood, 2012). The maximum 24-hour concentration of CO in our data set is equal to 3 ppm.

Table 3: Alternative models

Dependent variable	LS	LS	LS
SO_2 24 hrs. (ppb)	-0.0049*		-0.0081*
	(-1.977)		(-1.850)
$\ln(SO_2)$		-0.0158	
		(-1.370)	
ln (household income)		0.173***	0.289***
		(22.73)	(20.81)
Income	4.53e-7		
	(1.565)		
Weather variables			
Mean temperature (°C)	-0.0005	0.0004	-0.0003
	(-0.386)	(0.310)	(-0.144)
Temperature difference (°C)	0.0008	0.0007	-0.0002
	(0.320)	(0.280)	(-0.0415)
Rain (mm)	-0.0019	-0.0020*	-0.0030*
	(-1.571)	(-1.750)	(-1.750)
Snow (cm)	-0.0037	-0.0035	-0.0071
	(-0.996)	(-0.955)	(-1.088)
Cloud cover	0.094	0.00825	0.0102
	(0.529)	(0.450)	(0.340)
Constant	4.513***	2.737***	2.834***
	(47.12)	(15.13)	(11.28)
MWP to reduce SO_2 by 1 μg m^{-3}	\$4137(3371)	\$1464(1070)	\$841(457)
Socioeconomic covariates	Y	Y	Y
Month fixed effect	Y	Y	Y
Year Fixed effect	Y	Y	Y
Subdivision fixed effect	Y	Y	Y
Clusters	124	124	124
R-squared	0.074	0.094	
N	34587	34587	34587

See the footnotes to Table 2.

For NO_2, in the period 2000-2009, the total number of hours with pollution exceeding the maximum acceptable rate of 106 ppb per day is about 90 hours as indicated in Table 1. However, in our data set no respondent experienced a 24-hour pollution level of more than 69 ppb, and only 50 individuals had a 24-hour pollution of above 50 ppb. The threshold of 50 ppb is between the annual and 1-hour allowed level in the WHO guideline, and is also close to the 24-hours allowed level for NO_2 recommended by the United States Environmental Protection Agency.

For particulate matter ($PM_{2.5}$), referring to Table 1, NAPS sites recorded 1963 hours of pollution exceeding the threshold of 25 μg m^{-3} in the period 2000-2009. In our data set, about 2.5% of the respondents were exposed to above-threshold levels of $PM_{2.5}$. However, as can be seen in column 3 of Table 4, daily variations of this pollutant have no statistically significant effect on LS. One possible reason $PM_{2.5}$ not having any impact is the relatively stable level of this pollutant in each subdivision. As a result, the effect of such stationary pollution will be mostly captured by geographic fixed effects rather than the coefficient of $PM_{2.5}$ which shows the effect of transient levels of pollution. In fact, a comparison between the variance of $PM_{2.5}$ and SO_2 in different locations reveals that about 87% of the respondents live in subdivisions with a higher coefficient of variation (standard deviation over mean) for SO_2 compared to $PM_{2.5}$.

Columns 4 to 6 of Table 4 are related to the specifications that contain the alternative pollutants and SO_2. The coefficients of income have approximately the same value as in the first two columns. The coefficient of the alternative pollutant is again not statistically significant.

As mentioned earlier, the major health effects of SO_2 are caused by exposure to high concentrations of this pollutant. So, there is a possibility that higher pollution levels affect LS more than proportionally. On the other hand, the ratio of MWP to average income is similar to that from studies in locales with different average SO_2 levels, suggesting a rather constant marginal effect of pollution on LS. To check for a non-linear effect of SO_2 on LS, we use three different specifications. Column 1 of Table 5 contains a quadratic in SO_2 levels. The coefficient of SO_2 squared does not have the expected sign and is not statistically significant. Another form of non-linearity that can be considered is the exponential effect of pollution on LS. To test for this non-linear effect, we consider the regression of the log of LS as the dependent variable on pollution and the other covariates. With a significant coefficient of SO_2 and a relatively higher R-squared, it seems that this model captures the relation between pollution and LS. However, the dollar value of the MWP in this model is not significantly different from that of the baseline specification.

Column 3 of Table 5 is associated with a piecewise linear regression model with a breakpoint at the SO_2 level equal to 57 ppb. This is the maximum desirable level for the average 24-hours concentration of SO_2 in Canada. For a pollution level less than the threshold of 57 ppb, SO_2-l represents the pollution level, and SO_2-h is equal to 0. For a pollution level greater than the threshold, SO_2-l is equal to the threshold (57 ppb), and SO_2-h is the extra pollution over the threshold. As can be seen in column 3, the coefficient

Table 4: The effect of other pollutants on LS

Dependent variable	LS	LS	LS	LS	LS	LS
CO 24 hrs. (ppm)	0.0291			0.0192		
	(1.167)			(0.734)		
NO_2 24 hrs. (ppb)		7.4e-5			-8.2e-5	
		(0.057)			(-0.066)	
$PM_{2.5}$ 24 hrs. (ppm)			-0.0002			-0.0007
			(-0.220)			(-0.477)
SO_2 24 hrs. (ppb)				-0.0053	-0.0068*	-0.0050
				(-1.249)	(-1.848)	(-1.386)
ln (household income)	0.158***	0.164***	0.160***	0.169***	0.171***	0.170***
	(16.92)	(21.31)	(18.69)	(18.30)	(20.57)	(20.77)
Weather variables						
Mean temperature (°C)	0.0016	0.0003	0.0009	-0.0006	-0.0002	-0.00006
	(1.288)	(0.222)	(0.73)	(-0.381)	(-0.115)	(-0.05)
Temperature difference (°C)	-0.003	-0.0007	-0.0006	0.0017	0.0008	0.0112
	(-0.144)	(-0.442)	(-0.45)	(0.545)	(0.322)	(0.43)
Rain (mm)	-0.0033***	-0.0029**	-0.0029	-0.0032**	-0.0022*	-0.0022
	(-3.008)	(-2.342)	(-2.15)	(-2.527)	(-1.81)	(-1.63)
Snow (cm)	-0.0028	-0.0028	-0.0019	-0.0069	-0.0034	-0.0038
	(-0.867)	(-1.014)	(-0.72)	(-1.344)	(-0.814)	(-0.93)
Cloud cover	0.013	0.016	0.0145	0.0079	0.0078	0.0110
	(0.795)	(1.354)	(1.22)	(0.36)	(0.405)	(0.56)
Constant	2.882***	2.758***	2.890***	2.788***	2.732***	2.830***
	(19.16)	(19.34)	(19222)	(15.89)	(18.53)	(17.62)
MWP to reduce SO_2 by 1 μg m^{-3}				\$947(760)	\$1168(635)	\$870(627)
Socioeconomic covariates	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Year Fixed effect	Y	Y	Y	Y	Y	Y
Subdivision fixed effect	Y	Y	Y	Y	Y	Y
Clusters	115	171	175	79	100	103
R-squared	0.091	0.086	0.0868	0.098	0.095	0.0932
N	35080	50023	50997	24827	30581	30249

See the footnotes to Table 2.

of SO_2-h is not greater than that of SO_2-l and is not statistically significant. Consequently, there is no evidence that the pollution effect follows this form of non-linearity. The MWP values are close to what was obtained in Table 2.

Table 5: Testing for non-linear effect of pollution on LS

Dependent variable	LS	ln (LS)	LS
SO_2 24 hrs. (ppb)	-0.0069*	-0.0015**	
	(-1.815)	(-2.055)	
SO_2 squared	7.1e-5		
	(1.03)		
SO_2-l			-0.0053*
			(-1.968)
SO_2-h			-0.0015
			(-0.303)
ln (household income)	0.173***	0.049***	0.173***
	(21.86)	(21.06)	(21.84)
Weather variables			
Mean temperature (°C)	-0.0003	-0.0002	-0.0004
	(-0.271)	(-0.513)	(-0.281)
Temperature difference (°C)	0.0005	0.0003	0.0004
	(0.221)	(0.413)	(0.181)
Rain (mm)	-0.0020*	-0.0005	-0.0020*
	(-1.748)	(-1.514)	(-1.728)
Snow (cm)	-0.0036	-0.0008	-0.0036
	(-0.917)	(-0.735)	(-0.919)
Cloud cover	0.0090	0.0027	0.0089
	(0.486)	(0.510)	(0.484)
Constant	2.527***	0.995***	2.527***
	(17.12)	(23.03)	(17.09)
MWP to reduce SO_2 by 1 μg m^{-3}	\$1146(659)[a]	\$905(443)	\$914(466)
			\$250(827)
Socioeconomic covariates	Y	Y	Y
Month fixed effect	Y	Y	Y
Year Fixed effect	Y	Y	Y
Subdivision fixed effect	Y	Y	Y
Clusters	124	124	124
R-squared	0.088	0.14[b]	0.088
N	34587	34587	34587

See the footnotes to Table 2.

[a]In this model, the average MWP to reduce SO_2 by 1 μg m^{-3} is $\frac{\beta+2\gamma\overline{SO_2}}{\alpha}\bar{Y}$, where γ is the coefficient of the squared term and $\overline{SO_2}$ is the average SO_2 in the sample.

[b]To be comparable to the other specifications, the R-squared in this model is calculated using the predicted values for SWB rather than Ln(SWB).

We next test whether the effect of air pollution on well-being differs for respondents with different health status. In order to test for this, the respondents are divided into two groups depending on their Health Utilities Index (HUI). This measure of health, available in the CCHS data set, provides a description of an individual's 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 6 shows the results of the baseline specification for individuals with different health status. Column 1 is related to the respondents with good to perfect health (HUI$\geqslant$0.5), and column 2 is for the respondents with bad to severe health status (HUI$<$0.5). As can be clearly seen, air pollution is more critical for the individuals who are not in good health. The coefficient of SO_2 is about 5 times higher for this group of respondents. The MWP for air quality improvement is about 3.5 times higher for those with a poor health condition.

In the final part, we are interested to see whether air pollution 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 evaluating a person's satisfaction with life is usually a complex task since it involves gathering evidence for the assessment of whichever aspects of life, such as financial situation, family, and health, are salient to an overall evaluation, and then aggregating the evidence on those domains into a global evaluation using appropriate weights. This hypothetical procedure is a demanding and complex task, and available evidence is likely to include recent mood at the time of the interview. Such transitory experiences are a correct and valuable form of evidence, but may introduce a bias towards transitory influences including one-day conditions such as weather or pollution. In contrast, 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, rely on more sustained or objective evidence, albeit interpreted with subjective criteria.

Feddersen et al. (2012) find no effect from daily weather variation on domain-specific satisfaction, whereas there exists a significant effect on general LS. Table 7 contains our estimations of the baseline model (column 5 of Table 2), with various domain-specific satisfactions as the dependent variable. In the CCHS, the respondents are asked about their level of satisfaction with health, job, leisure activities, financial situation, friends, and housing. The possible answer to any of these questions is one of five levels of satisfaction ranging from very dissatisfied to very satisfied. As can be seen in Table 7, there is no statistically significant effect of SO_2 concentration on any of these satisfaction measures.

On the other hand, our estimated standard errors cannot reject effects about as large as we find for life satisfaction. One might not expect an effect of pollution on satisfaction with finances, in which case this estimate may serve as a placebo test of our method. Conversely, the effect of pollution may be expected to impact on health, leisure, or other domains. Our results can only reject the hypothesis of a much stronger effect on any particular domain than we find for life satisfaction.

Table 6: The effect of pollution on individuals with different health status

Dependent variable	LS HUI$\geq$ 0.5	LS HUI$<$ 0.5
SO_2 24 hrs. (ppb)	-0.0042*	-0.023*
	(-1.815)	(-2.055)
ln (household income)	0.165***	0.141
	(22.31)	(1.591)
Weather variable		
Mean temperature (°C)	-1.5e-5	-0.010
	(-0.0093)	(-1.224)
Temperature difference (°C)	0.0012	-0.0176
	(0.522)	(-1.217)
Rain (mm)	-0.0015	-0.019**
	(-1.435)	(-2.288)
Snow (cm)	-0.0027	-0.0022
	(-0.741)	(-0.074)
Cloud cover	0.0128	-0.0965
	(0.732)	(-1.090)
Constant	2.730***	3.266***
	(19.55)	(3.34)
MWP to reduce SO_2 by 1 μg m^{-3}	$753(451)	$2658(2340)
Socioeconomic covariates	Y	Y
Month fixed effect	Y	Y
Year Fixed effect	Y	Y
Subdivision fixed effect	Y	Y
Clusters	123	55
R-squared	0.087	0.276
N	33699	888

See the footnotes to Table 2.

Table 7: The effect of pollution on domain specific satisfaction

Dependent variable	Satisfaction health	Satisfaction job	Satisfaction leisure	Satisfaction financial sit.	Satisfaction friends	Satisfaction housing
SO_2 24 hrs. (ppb)	-0.0013	0.0044	-0.0022	0.0028	-0.0006	-0.0034
	(-0.380)	(1.411)	(-0.484)	(0.760)	(-0.181)	(-0.938)
ln (household income)	0.177***	0.187***	0.168***	0.421***	0.111***	0.204***
	(12.18)	(7.808)	(9.776)	(22.62)	(7.388)	(11.06)
Weather variables						
Mean temperature (°C)	-0.00124	0.0032	0.0059	0.0008	-0.0003	-0.0057
	(-0.999)	(1.246)	(1.601)	(0.182)	(-0.154)	(-1.584)
Temperature difference (°C)	-0.0003	0.0026	0.0091**	0.0034	-0.0061	-0.0070*
	(-0.112)	(0.536)	(2.420)	(0.465)	(-1.210)	(-1.960)
Rain (mm)	-0.0011	-0.0002	0.001	-0.0047	-0.0033	-0.0027
	(-0.803)	(-0.048)	(0.339)	(-1.199)	(-1.432)	(-1.214)
Snow (cm)	-0.0087**	-0.0021	-0.0025	-0.0062	-0.0064*	-0.016***
	(-2.30)	(-0.588)	(-0.538)	(-1.144)	(-1.795)	(-3.344)
Cloud cover	0.018	0.0099	0.068*	0.029	3.64e-5	-0.022
	(0.907)	(0.282)	(1.936)	(0.670)	(0.0015)	(-0.639)
Constant	1.733***	1.956***	3.118***	0.552	***3.460	***3.02
	(8.73)	(6.62)	(9.40)	(1.58)	(14.71)	(10.55)
Socioeconomic covariates	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Year Fixed effect	Y	Y	Y	Y	Y	Y
Subdivision fixed effect	Y	Y	Y	Y	Y	Y
Clusters	124	70	70	70	70	70
R-squared	0.146	0.081	0.077	0.173	0.065	0.097
N	34587	8450	8450	8450	8450	8450

See the footnotes to Table 2.

5 Reduction of SO_2 pollution in Canada

Canada has decreased per capita SO_2 emissions by 34% from 1990 to 2009. This has resulted in a not great improvement in air quality considering the 20% population increase in the same period. Emission reduction in Canada is lower compared to countries such as Germany and the UK, which had 92% and 90% reduction per capita respectively from 1990 to 2009 (Vestreng et al., 2007). Canada also ranks second among the major OECD countries in per capita SO_2 emission. The largest sources of SO_2 emissions such as electricity generators, petroleum refineries, smelting, and other industrial sources are the subject of policies and legislation in different countries. For example, Germany obtained its improvement through replacing old combustion facilities, desulfurization of flue gases in large combustion plants, and switching from solid to gaseous and liquid fuels (Vestreng et al., 2007).

SO_2 emissions in Canada have been subject to international protocols or national and provincial agreements since 1985. According to the Canadian Council of Ministers of the Environment report on acid rain (CCME, 2011, pg. 21-33), most provinces met the provincial caps of 2010 by 2008. However, Canada's threshold for one-day SO_2 concentration is substantially higher than the WHO guideline level (see the last two columns of Table 1). In fact, the difference between Canadian and WHO thresholds is the largest for SO_2 among all the major pollutants. Using the MWP for pollution reduction obtained above, it is possible to estimate the imposed costs to the population from Canada's higher threshold setting. We calculate the imposed costs to the individuals who were exposed to levels above the WHO threshold pollution for a relatively large number of days. We consider the stations that had more than 150 days with one-day average SO_2 above the WHO threshold (8 ppb) in the period of 2005-2011.

From the total number of 290 monitoring stations, 25 stations had more than 150 days with an SO_2 concentration above the WHO threshold. Table 8 lists these stations along with the average pollution in polluted days. For these monitoring stations, we consider the population of the census subdivision in which any station is situated as the affected population.[6] For these individuals, the imposed costs from SO_2 pollution are approximated by the willingness to pay to reduce the pollution down to the WHO threshold, which is approximately $720 million per year.

As mentioned earlier, electricity generators are one of the major emitters of SO_2. In Canada, about 20% of total produced electricity is generated in thermal plants. Coal-burning power plants produce approximately 64% of total electricity from these thermal plants. Due to negative environmental impacts of coal-fired generation, Canada has set a stringent performance standard for new coal units. Additionally, faced with an aging coal-fired electricity generating fleet, it is expected that a number of old coal units will be shut down gradually. Although according to Canadian regulations, the first units are going

[6]Most of the highly polluted subdivisions are small with individuals living within 5 km of the monitoring station. In a few larger subdivisions, we consider only the individuals in an area of 25 km^2 as the affected population (It is assumed that population is uniformly distributed over these subdivisions.).

to be closed by 2020, a number of units in Ontario and Saskatchewan will be closed prior to this date due to provincial acts.

The Ontario Green Energy and Green Economy Act (GEA) was passed in May 2009 to address environmental concerns. To comply with this act, Ontario has gradually replaced coal power generation with a mix of emission-free energy sources like nuclear and renewables, along with lower-emission sources such as natural gas. While, in 2003, coal accounted for 25% of electricity generation, coal-fired generation made up less than 3% of Ontario's total electricity generation in 2011. Ontario closed the last coal units in the province at the end of 2013. These last units belong to Nanticoke power generation plant located in Haldimand County in southern Ontario, which used to be one of Canada's largest greenhouse gas emitters and the second highest emitter of sulfur dioxide.

One of the benefits of closing Nanticoke power plant is reducing the concentration of different pollutants such as CO_2, SO_2, and mercury. An accurate cost-benefit analysis in this case needs an estimation of the impacts on electricity price as well as job losses from the plant shutting down. To estimate the effect of change in SO_2 concentration, the difference between average daily pollution before and after closure should be considered. The nearest monitoring station to Nanticoke is 22 km away. So, it is not possible to obtain the daily SO_2 level in the areas very close to the plant that are mostly affected by pollution. However, using the MWP for SO_2 reduction derived from our regression analysis, the marginal benefit only from the decrease in SO_2 concentration by 1 μg m^{-3} in Haldimand County is about $40 million per year.

Table 8: List of the stations recorded more than 150 days of daily SO_2 concentration above the WHO threshold (8 ppb) in 2005-2011

Station	No. of days with average SO_2>8 ppb	Average SO_2 concentration in polluted days (ppb)
Trail	1147	18
Temiscaming	748	34
Saguenay	578	24
Sarnia	562	21
Flin Flon	496	33
Prince George	475	16
Chetwynd	456	15
Port aux Choix	422	28
Hamilton	373	14
Prince George	367	14
Port Alice	342	17
Montreal	338	15
Windsor	321	12
St Joseph de Sorrel	310	34
Redwater	300	22
Saint John	287	17
Sorel-Tracy	248	19
Kitimat	246	14
Port Alice	238	25
Halifax	235	17
Shawinigan	201	20
Robson	182	15
Charlottetown	173	12
Rouyn Noranda	157	14

6 Conclusion

In the last decades, environmental policies and regulations in developed countries have led to a great improvement in air quality. What justifies the implementation of these policies and regulations, which have been costly mostly for the first generation affected by new regulations, is the ultimate effect on welfare. A number of studies try to estimate this impact on individuals' welfare from an economic point of view. Various recent approaches use non-market methods of evaluation, and among these, there is a growing interest in the life satisfaction approach (LSA) as a way to evaluate impacts in all-encompassing terms. This is due to the recent progress in subjective well-being (SWB) research and access to surveys of self-reported life satisfaction (LS) as an empirical approximation of individuals' welfare.

In this study we quantify the extent to which the day-to-day variation of air pollution is reflected in individuals' life satisfaction. Our analysis supports the finding of previous literature that life satisfaction contains useful information about individuals' preferences. More precisely, we find that air pollution measured by the 24-hours concentration of SO_2 has an effect on self-reported life satisfaction. However, when there is no control for individuals' socioeconomic attributes or weather, it is not possible to reject that daily variation of pollution is not noticed by individuals. After controlling for socioeconomic characteristics and weather, the impact of daily pollution is robust to a number of specifications and is also identified in two groups of respondents with different health status. As expected, the adverse effect of pollution on well-being is considerably higher for individuals having a poor health condition.

Using the life satisfaction approach also gives the opportunity to monetize the value of environmental conditions. The estimated coefficients for air pollution and income can be used to obtain the implicit marginal willingness to pay for air quality changes. In our analysis, the proportion of average annual income that compensates for the negative effects of a marginal increase in pollution is substantial. According to our baseline specifications, implicit willingness to pay to decrease SO_2 concentration by 1 μg m^{-3} throughout the year is about 1.1% of Canadians' average annual household income. The compensating differential for an increase in SO_2 level by one-half standard deviation is about 4.4% of the average household income.

This value may sound, at first, enormous given that it relates to a single amenity on a short time scale. A large compensating differential does not, however, imply a large behavioural willingness to pay. Rather than measuring behavioural preferences, the large compensating differential suggests that people would experience higher well-being if pollution was lower. The magnitude of this equivalence reflects the relatively small coefficient we estimate on log of income, which suggests that a factor three rise in income accounts for only 0.2 increase in life satisfaction on a five-point scale. This estimate is entirely consistent with an extensive body of literature which also finds large income-equivalent effects of other non-financial aspects of life satisfaction (MacKerron, 2011; Dolan et al., 2008; Helliwell and Wang, 2013). However, even if the subjective measure of life satisfaction is taken as an appropriate, or the ultimate, measure of experienced well-being, one may further probe the specific channels by which pollution makes lives worse, overall. On this, our study sheds little light, except for our evidence on the extra susceptibility of those with weaker health.

In the period 1990-2009, Canada decreased per capita SO_2 emission by 34%. This is not a great improvement considering a 20% population increase and an above 90% emission reduction in countries such as Germany and the UK in the same period. SO_2 emissions in Canada have been subject to regulation enforcing international protocols or national and provincial agreements since 1985. While most provinces met the provincial caps of 2010 by 2008, our analysis still shows a significant adverse effect of SO_2 on Canadians' well-being, which imposes a great cost specifically on the population in the polluted areas. This implies a possible need for stricter regulations that speed up the compliance of provinces with lower caps for emission. The results of studies such as the present one can help policy makers in developing better cost-benefit analysis of environmental regulations. Achievements like Ontario's closure of the last coal-fired power plant by the end of 2013 could be justified despite the increase in the electricity price and job losses.

Table 9: Summary of variables

Variable	Obs.	Mean	Std. Dev.
Satisfaction-Life	322233	4.28	0.70
Satisfaction-health	322233	3.71	0.98
Satisfaction-job	70998	4.16	0.86
Satisfaction-financial situation	70998	3.70	1.04
Satisfaction-friends	70998	4.36	0.69
Satisfaction-housing	70998	4.29	0.81
Household income	322233	79504.33	79658.43
Health Index	107382	0.89	0.18
Age	322233	43.55	17.98
Female (dummy)	322233	0.49	0.50
Male (dummy)	322233	0.51	0.50
Married (dummy)	322233	0.49	0.50
Common-law (dummy)	322233	0.11	0.32
Widowed (dummy)	322233	0.04	0.20
Separated (dummy)	322233	0.03	0.16
Divorced (dummy)	322233	0.05	0.22
Single (dummy)	322233	0.27	0.44
At work last week (dummy)	322233	0.60	0.49
Absent last week (dummy)	322233	0.05	0.22
No job last week (dummy)	322233	0.24	0.43
Unable permanently to work (dummy)	322233	0.02	0.14
Less than secondary (dummy)	322233	0.06	0.25
Secondary graduate(dummy)	322233	0.10	0.30
Some post secondary (dummy)	322233	0.05	0.22
Post secondary graduate (dummy)	322233	0.73	0.44
Daily SO_2	55324	1.69	3.18
Daily NO_2	80893	13.27	8.18
Daily $PM_{2.5}$	88124	7.35	6.42
Daily CO	52110	0.22	0.22
Mean Temperature	175141	7.22	10.74
Temperature difference	175141	9.79	4.33
Rain	142295	2.25	5.98
Snow	143041	0.47	2.12
Cloud cover	167349	3.44	0.60

References

Atkinson, R. W., S. A. Bremner, and H. R. Anderson (1999). Short-term associations between emergency hospital admissions for respiratory and cardiovascular disease and outdoor air pollution in london. *Archives of Environmental Health 54*(6), 398 – 411.

Barrington-Leigh, C. P. (2009). Geography, reference groups, and the determinants of life satisfaction. *PH.D. Thesis. University of British Columbia*.

Bentham, J. (1789). *An introduction to the principles of morals and legislation.* (Reprinted 1948, Oxford, UK: Blackwell).

Brereton, F., J. P. Clinch, and S. Ferreira (2008). Happiness, geography and the environment. *Ecological Economics 65*(2), 386 – 396.

Bullinger, M. (1989). Psychological effects of air pollution on healthy residents, a time-series approach. *Journal of Environmental Psychology 9*(2), 103–118.

Carlsson, F. and O. Johansson-Stenman (2000). Willingness to pay for improved air quality in sweden. *Applied Economics 32*(6), 661–669.

CCME (2011). 2008-2009 progress report on the canada wide acid rain strategy for post 2000.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? evidence from the housing market. *Journal of Political Economy 113*(2).

Depro, B., C. Timmins, and M. O'Neil (2015). White flight and coming to the nuisance: Can residential mobility explain environmental injustice? *Journal of the Association of Environmental and Resource Economists 2*(3), 439–468.

Di Tella, R. and R. MacCulloch (2006). Some uses of happiness data in economics. *The Journal of Economic Perspectives*, 25–46.

Di Tella, R. and R. MacCulloch (2008). Gross national happiness as an answer to the easterlin paradox? *Journal of Development Economics 86*(1), 22 – 42.

Diamond, P. A. and J. A. Hausman (1994). Contingent valuation: Is some number better than no number? *The Journal of economic perspectives 8*(4), 45–64.

Diener, E. (1984). Subjective well-being. *Psychological Bulletin* (95), 542–575.

Dolan, P., T. Peasgood, and M. White (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology 29*(1), 94–122.

Ehrhardt, J. J., W. E. Saris, and R. Veenhoven (2000). Stability of life-satisfaction over time. *Journal of Happiness Studies 1*(2), 177–205.

Feddersen, J., R. Metcalfe, and M. Wooden (2012). Subjective well-being: Weather matters; climate doesn't. *Melbourne Institute Working Paper*.

Ferreira, S. and M. Moro (2010). On the use of subjective well-being data for environmental valuation. *Environmental and Resource Economics 46*(3), 249–273.

Ferrer-i Carbonell, A. and P. Frijters (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal 114*(497), 641–659.

Frey, B., S. Luechinger, and A. Stutzer (2009). The life satisfaction approach to valuing public goods: The case of terrorism. *Public Choice 138*, 317–345.

Frey, B. S., S. Luechinger, and A. Stutzer (2010). The life satisfaction approach to environmental valuation. *Annual Review of Resource Economics 2*(1), 139–160.

Frey, B. S. and A. Stutzer (2002). What can economists learn from happiness research? *Journal of Economic literature*, 402–435.

Fujita, F. and E. Diener (2005). Life satisfaction set point: stability and change. *Journal of personality and social psychology 88*(1), 158.

Helliwell, J. and S. Wang (2013). World happiness: Trends, explanations, and distribution. In J. Helliwell, R. Layard, and J. Sachs (Eds.), *World Happiness Report*, Chapter 2, pp. 58–37. United Nations.

Kahneman, D. (2000). Experienced utility and objective happiness: A moment-based approach. *Choices, values, and frames*, 673–692.

Kahneman, D. and J. L. Knetsch (1992). Valuing public goods: the purchase of moral satisfaction. *Journal of environmental economics and management 22*(1), 57–70.

Katsouyanni, K., G. Touloumi, C. Spix, J. Schwartz, F. Balducci, S. Medina, G. Rossi, B. Wojtyniak, J. Sunyer, L. Bacharova, et al. (1997). Short-term effects of ambient sulphur dioxide and particulate matter on mortality in 12 european cities: results from time series data from the aphea project. air pollution and health: a european approach. *BMJ: British Medical Journal 314*(7095), 1658.

Kelman, M. (2005). Hedonic psychology and the ambiguities of welfare. *Philosophy and Public Affairs 33*(4), 391–412.

Levinson, A. (2012). Valuing public goods using happiness data: The case of air quality. *Journal of Public Economics 96*(9 - 10), 869 – 880.

Luechinger, S. (2009). Valuing air quality using the life satisfaction approach. *The Economic Journal 119*(536), 482–515.

Luechinger, S. (2010). Life satisfaction and transboundary air pollution. *Economics Letters 107*(1), 4 – 6.

MacKerron, G. (2011). Happiness economics from 35000 feet. *Journal of Economic Surveys*.

MacKerron, G. and S. Mourato (2009). Life satisfaction and air quality in london. *Ecological Economics 68*(5), 1441 – 1453.

Partti-Pellinen, K., O. Marttila, V. Vilkka, J. J. K. Jaakkola, P. Jappinen, and T. Haahtela (1996). The south karelia air pollution study: Effects of low-level exposure to malodorous sulfur compounds on symptoms. *Archives of Environmental Health: An International Journal 51*(4), 315–320.

Pavot, W. and E. Diener (1993). Review of the satisfaction with life scale. *Psychological assessment 5*(2), 164.

Rehdanz, K. and D. Maddison (2008). Local environmental quality and life-satisfaction in germany. *Ecological Economics 64*(4), 787 – 797.

Rotton, J. (1983). Affective and cognitive consequences of malodorous pollution. *Basic and Applied Social Psychology 4*(2), 171–191.

Schwarz, N. and F. Strack (1991). Evaluating one's life: A judgment model of subjective well-being. *Subjective well-being: An interdisciplinary perspective 21*, 27–47.

Schwarz, N., F. Strack, D. Kommer, and D. Wagner (1987). Soccer, rooms, and the quality of your life: Mood effects on judgments of satisfaction with life in general and with specific domains. *European Journal of Social Psychology 17*(1), 69–79.

Sumner, L. W. (1996). *Welfare, happiness and ethics*. Oxford University Press.

Szyszkowicz, M. (2008). Air pollution and daily emergency department visits for headache in montreal, canada. *Headache: The Journal of Head and Face Pain 48*(3), 417–423.

Vestreng, V., G. Myhre, H. Fagerli, S. Reis, L. Tarrason, et al. (2007). Twenty-five years of continuous sulphur dioxide emission reduction in europe. *Atmos. Chem. Phys 7*(13), 3663–3681.

Welsch, H. (2002). Preferences over prosperity and pollution: Environmental valuation based on happiness surveys. *Kyklos 55*(4), 473–494.

Welsch, H. (2006). Environment and happiness: Valuation of air pollution using life satisfaction data. *Ecological Economics 58*(4), 801 – 813.

Wood, J. (2012). Canadian environmental indicators - air quality. *Fraser Institute*.

World Health Organization (2006). *Air Quality Guidelines: Global Update 2005. Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide*. World Health Organization.

Zivin, J. G. and M. Neidell (2013, September). Environment, Health, and Human Capital. *Journal of Economic Literature 51*(3), 689–730.