Essays in Environmental Economics: The well-being impacts of environment and optimal resource extraction

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Abstract

Life satisfaction has been widely used in recent years for evaluating the welfare impacts of the environment. In Chapters 1 and 2, the effect of a number of environmental factors on well-being is studied. In Chapter 1, a set of repeated cross-sectional surveys is combined with high-resolution pollution and weather data. The respondents' level of life satisfaction is modeled as a function of their socioeconomic characteristics and income as well as the weather and air pollution on the day of the survey interview. In order to overcome endogeneity problems, a set of high-resolution geographic fixed effects is included in all specifications. The empirical analysis in this chapter 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.

The empirical analysis in Chapter 2 is on two major health surveys in Canada, namely the Canadian Community Health Survey (CCHS) and the National Population Health Survey (NPHS). In this chapter, it is shown that, after controlling for individuals' socioeconomic characteristics, temporal weather variations have a statistically significant effect on satisfaction with life. This effect is identified in a number of alternative specifications. Women and

individuals with poor health conditions are more affected by weather conditions. Although statistically significant, the effect of weather on life satisfaction is small compared to the major socioeconomic determinants of well-being. Confirming the results of past studies, the analysis of the repeated cross-sectional data shows the impact of long-term climate variables on life satisfaction.

Most studies on the dynamic game of exhaustible resources rely on analytical solutions to find the equilibrium. In Chapter 3, numerical approaches to finding the feedback and the open-loop equilibriums are applied to examine the robustness of the results of a number of studies that were limited to analytical solutions. In this chapter, first the analysis in Salo and Tahvonen (2001), which assumes an economic depletion of resources, is extended to the case of an iso-elastic demand combined with reserve-dependent costs by applying two different numerical methods. In addition, the open-loop equilibrium is derived numerically and the results are compared with those of the feedback equilibrium. We examine separately the cases with identical costs and cost asymmetry among producers. Next, the study of Benchekroun and Van Long (2006) on the impact of an increase in resource stock is extended by considering production costs. It is shown that, with non-zero costs, the high-cost firms might face a decrease in profit as a result of a resource increase.

Résumé

La satisfaction à l'égard de la vie a été largement utilisée au cours des dernières années pour évaluer les impacts sociaux de l'environnement. Dans les chapitres 1 et 2, l'effet d'un certain nombre de facteurs environnementaux sur le bien-être est étudié. Dans le chapitre 1, les données de plusieurs cycles d'une enquête transversale sur la santé sont combinées avec des données à haute résolution sur la pollution de l'air et des données météorologiques. Le niveau de satisfaction à l'égard de la vie des répondants est modélisé comme une fonction de leurs caractéristiques socio-économiques et revenus ainsi que de la pollution de l'air et la météo le jour de l'entrevue de l'enquête. Afin de surmonter les problèmes d'endogénéité, un ensemble d'effets fixes géographiques de haute résolution est inclus dans toutes les spécifications. L'analyse empirique dans ce chapitre suggère que même lorsque l'on neutralise les effets fixes locaux et saisonniers, une pollution de l'air plus élevée réduit considérablement la satisfaction à l'égard de la vie. L'effet négatif de l'augmentation transitoire de la pollution de l'air est plus important pour les individus avec un mauvais état de santé. L'estimation du différentiel de compensation moyenne entre le revenu et la pollution de l'air montre que la valeur de l'amélioration de la qualité de l'air par un demi écart-type par année est d'environ 4.4 % du revenu annuel moyen des Canadiens.

L'analyse empirique dans le chapitre 2 porte sur plusieurs cycles de deux grandes enquêtes de santé au Canada, à savoir l'Enquête sur la santé dans les collectivités canadiennes (ESCC)

et l'Enquête nationale sur la santé de la population (ENSP). Dans ce chapitre, il est montré que, après le contrôle pour les caractéristiques socio-économiques des individus, les variations climatiques temporelles ont un effet statistiquement significatif sur la satisfaction à l'égard de la vie. Cet effet est identifié dans un certain nombre de spécifications différentes. Les femmes et les personnes en mauvais état de santé sont plus affectées par les conditions météorologiques. Bien que statistiquement significatif, l'effet des conditions météorologiques sur la satisfaction à l'égard de la vie est faible par rapport aux principaux déterminants socio-économiques du bien-être. Confirmant les résultats d'études antérieures, l'analyse des données transversales montre l'impact des variables climatiques à long terme sur la satisfaction à l'égard de la vie.

La plupart des études du jeu dynamique des ressources épuisables s'appuient sur des solutions analytiques pour trouver l'équilibre. Dans le chapitre 3, les approches numériques pour trouver les équilibres en feedback et en boucle ouverte sont appliquées à étendre l'analyse d'un certain nombre d'études qui ont été limitées à des solutions analytiques. Dans ce chapitre, d'abord l'analyse de Salo et Tahvonen (2001), qui suppose un appauvrissement économique des ressources, est étendue au cas d'une demande iso-élastique combinée avec des coûts qui dépendent du niveau de réserve par l'application de deux méthodes numériques différentes. En outre, l'équilibre en boucle ouverte est dérivé numériquement et les résultats sont comparés avec ceux de l'équilibre en feedback. Les simulations sont répétées supposant l'asymétrie des coûts entre les producteurs. Ensuite, l'étude de Benchekroun et Long (2006) sur l'impact d'une augmentation du stock de ressources est étendue en tenant compte des coûts de production et en utilisant des approches numériques. Il est montré que, avec des coûts non nuls, les entreprises à coûts élevés pourraient faire face à une diminution des profits en raison d'une augmentation des ressources.

Contribution of authors

Each of the chapters of this thesis represents a co-authored paper; however the work that led to this completed thesis (empirical analysis and simulation) is primarily my own.

The first two chapters are co-authored with Professor Christopher Barrington-Leigh. The literature review, data gathering, empirical analysis, and writing are mainly my own work. Professor Barrington-Leigh initialized the research idea and provided advice and direction on data gathering, empirical analysis, and interpretation of the results. He also provided advice on writing both chapters and commented on revisions.

The third chapter is co-authored with Professor Hassan Benchekroun. The main part of numerical method design, computer programming, simulations and the writing are mainly my own work. Professor Benchekroun initialized the research idea and provided advice on the application of numerical methods and commented on writing the chapter.

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Introduction

Over the past four decades, researchers have studied a variety of subjects in Environmental Economics. While the initial concerns in the field were about the problem of adequacy of exhaustible resources and their optimal extraction, recently more attention has been devoted to the design and the effects of environmental policies. The subjects investigated in this thesis are related to both optimal resource use and the welfare impacts of environment. Chapters 1 and 2 are related to more recent environmental concerns and include empirical studies on the impact of environment on individuals' well-being. The third chapter of this thesis is aimed to apply a number of numerical approaches to derive equilibriums in a dynamic game of exhaustible resource oligopoly.

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.

The majority of the empirical economic studies in the field of subjective well-being are based on the respondents answering a question about a global self-reported measure of life satisfaction; see, for example Frey et al. (2010) for a review of studies on the impact of air pollution on life satisfaction. In most surveys, life satisfaction is derived from individuals' responses to the following question: How satisfied are you with your life in general? Respondents are asked to choose from one of the numerically ordered satisfaction levels ranging from very satisfied to very dissatisfied.

In recent years, there has been an increasing amount of literature concerning the validity, reliability, and inclusiveness of life satisfaction measures. Studies in this area have addressed the different causes of skepticism towards using survey-reported global life satisfaction and have shown that life satisfaction can serve as a valid approximation of individuals' welfare. If this interpretation of life satisfaction is accepted, it is possible to find the impact of different factors affecting well-being. These factors are broadly categorized into individuals' characteristics and the attributes related to the environment in which they are living. The impact from any of these determinants on well-being can then be obtained empirically. This can be done by assuming life satisfaction to be a function of its different determinants and statistically estimating the impact of each factor in a representative sample of any population. Using this approach, I look at the impact of some aspects of the environment on individuals' well-being in Chapters 1 and 2. While the focus in Chapter 1 is on air pollution, Chapter 2 is about the effect of weather variations on well-being.

The main concern in Chapter 1 is first to estimate the impact of daily variation of air pollution on life satisfaction as a measure for individuals' welfare and then obtain individuals' willingness to pay for better air quality. After estimating the impact of different covariates on life satisfaction, the marginal impact of air pollution and income can be used to obtain the value of air quality to individuals. The value of a marginal change in air quality is equal to the marginal rate of substitution between income and pollution when utility, represented by life satisfaction, is constant. This approach to calculating a monetary value for a public good is known as the life satisfaction approach (LSA). The life satisfaction approach has a number of advantages over both approaches of contingent valuation and hedonic pricing, which are the well-known methods for public goods valuation (Frey et al., 2010). This approach has been used in a number of studies to obtain the value of air quality. Frey et al. (2010) contains a review of the studies on air quality valuation using the life satisfaction approach.

The study in Chapter 1 is the first study on the relation between life satisfaction and air pollution in Canada. The data used in this work is from six cycles of the Canadian Community Health Survey (CCHS), which is the largest cross-sectional health data in Canada. In this chapter, first it is shown that, after accounting for individuals' socioeconomic characteristics as well as geographic and seasonal fixed effects, the day-to-day variations of sulfur dioxide (SO_2) concentration have a statistically significant effect on life satisfaction. This effect is robust to a variety of empirical specifications as well as estimations for different health groups. It is also shown that individuals' life satisfaction is not related in sensible ways to the daily variation of other major pollutants, namely carbon monoxide (CO), nitrogen dioxide (NO_2), and fine particulate matter ($PM_{2.5}$).

In psychological studies, it is claimed that self-evaluation of satisfaction in specific areas, such as job or leisure, is less cognitively demanding than evaluating life as a whole. Individuals are less prone to refer to their moods at the time of interview while reporting these types of satisfaction (Schwarz and Strack, 1991). In the last specification in Chapter 1 it is shown that the effect of daily SO_2 concentration on a set of domain-specific satisfactions is not significantly different from zero.

Canada has decreased its per capita SO_2 emission by 34% in the period 1990-2009. However, the concentration of this pollutant is higher than the WHO threshold in the areas close to thermal power plants and a number of industrial regions. In the final part of Chapter 1, using the marginal willingness to pay to reduce SO_2, it is shown that decreasing SO_2 emission in highly polluted areas down to the WHO threshold will increase individuals' welfare to a great extent.

In Chapter 2, I focus on the impact of transient weather on life satisfaction. Most studies consider the impact of weather on individuals' mood as the channel through which weather affects life satisfaction. Referring to current moods and feelings has an impact in reporting life satisfaction as a general judgment about one's life as a whole. The reason is that evaluating one's life as a whole is very cognitively demanding and individuals might simply choose to refer to their current feelings at the time of the interview. The impacts from the transitory factors of this type impose no systematic bias in estimations since such impacts are not correlated across individuals. The weather variations, however, might have an effect on LS which might be correlated across individuals. The relevance of weather covariates in reporting life satisfaction has been shown in a number of recent studies. The statistically significant weather variables in these studies are recent cloudiness (Barrington-Leigh, 2009), temperature (Levinson, 2012), and precipitation and temperature (Connolly, 2013).

The main data sets used in this study are the Canadian National Population Health Survey (NPHS) and the Canadian Community Health Survey (CCHS). Using both panel and cross-sectional 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.

The results of the OLS estimations show that the impact of daily rainfall on life satisfaction is statistically significant in the cross-sectional and pooled panel data. If total daily rainfall is one standard deviation (6 mm) above its average, LS decreases by approximately 0.01 on a five-point scale of 1 to 5, according to the most preferred estimation. This result is robust to a number of alternative specifications such as an ordered probit model. It is also shown that females and individuals with poor health conditions are more affected by weather changes.

Regarding the relative impact of weather compared to the other variables, we first show that accounting for weather variations in the estimations has a negligible impact on the coefficients of the major life satisfaction determinants. When weather variations are accounted for, the marginal effect of day-to-day variations in rainfall has an impact similar to a 1% change in household income. This impact is relatively low compared to the effect of major determinants of life satisfaction such as income and employment status. Accounting for weather is necessary only when estimating the effect of the variables, such as air pollution, that are correlated with both life satisfaction and weather conditions.

The sensitivity of domain-specific satisfactions to weather variables is tested by a number of regressions with different satisfactions as dependent variables. Considering all domain-specif regressions, the number of significant weather coefficients is approximately equal to what is expected to be randomly significant at 10% level. This indicates that a less cognitively demanding satisfaction evaluation is not affected by transient factors such as weather.

Finally, I look at the relevance of climate and life satisfaction. The results of the specifications in the cross-sectional and the pooled panel data indicate that there is a relation between a number of long-term climate variables and life satisfaction. When individual fixed effects are controlled for in our panel data, only a small set of climate variables is found to be significant, suggesting that the direct impact of climate on LS might be very small. However, further statistical analysis on large panel data sets is necessary to test if climate directly affects life satisfaction. While in the first two chapters the focus is on relatively recent concerns in environmental economics, the third chapter is devoted to studying the competition in the market of exhaustible resources which is among the earlier subjects in the field.

The studies that analyze the exhaustible resource market within a dynamic game framework can be divided into the two broad categories of common and non-common resources. My focus in the third chapter is on the latter category, in which each producer extracts its own resource but supplies on the same market as the other producers. In the third chapter, I use numerical approaches to examine the generality of existing results in exhaustible resource oligopoly that were established analytically but under very specific demand and/or cost functions.

In the dynamic game literature there is a distinction between open-loop and feedback equilibriums (Dockner, 2000; Haurie et al., 2012). In the open-loop equilibrium, each player determines its optimal extraction at all time knowing the path of extraction of all the other players. So, the equilibrium strategy, which is only time-dependent, can be determined at the initial time. In this equilibrium, if one of the players deviates from its equilibrium strategy, it is, in general, not optimal for the rest of the players to follow their equilibrium strategy.

Different supply-side market structures such as duopoly, cartel-fringe, and oligopoly as well as various assumptions for extraction costs have been examined under the assumption that firms use open-loop strategies. Long (2010) reviews the studies using an open-loop approach in the exhaustible resource market. Deriving equilibrium strategies in the open-loop case is relatively simple compared to the feedback case. However, the assumption of precommitment of producers to a binding path of extraction cannot be met in reality if at least one firm deviates from the equilibrium strategy.

The studies using open-loop strategies usually consider simple forms of demand and cost functions and find the equilibrium strategy analytically by applying the maximum principle; see for example Loury (1986), Gaudet and Long (1994), and Benchekroun et al. (2010). The system of differential equations that characterizes equilibrium, however, can seldom be solved analytically.

As opposed to open-loop strategies, feedback strategies depend only on resource level. Finding a feedback equilibrium analytically is more difficult compared to the open-loop equilibrium. In fact, the analytical solution has been determined in a few special cases, such as iso-elastic demand combined with zero costs (Benchekroun and Van Long, 2006), and linear demand and linear unit costs with economic depletion (Salo and Tahvonen, 2001). In the case of economic depletion, the complete physical depletion of a resource is not profitable since the reserve-dependent production costs will be greater than the resource price after the reserve reaches a certain level. Salo and Tahvonen (2001) is, to the best of my knowledge, the only study that addresses a numerical solution for the resource extraction problem in the dynamic game of exhaustible resources. Their approach is based on policy iteration and Markov approximation of value function.

In this chapter, first I extend the analysis in Salo and Tahvonen (2001) to the case of an iso-elastic demand together with a cost function that depends on the resource level. This demand function is later used in this chapter to extend the study of Benchekroun and Van Long (2006) on the effect of resource increase on producers' profit. The equilibrium strategy and the pattern of resource use obtained in this case confirm the results of Salo and Tahvonen (2001) on relative share of producers. With reserve-dependent costs and under economic depletion, the share of the producer with lower reserves increases with time. This result does not correspond to the models such as "oil'igopoly" in Loury (1986) where the share of the high resource producer increases with time. Using a numerical approach to derive the open-loop equilibrium, the path of extraction and the change in relative share of producers are obtained and compared with those of feedback cases for the functions in Salo and Tahvonen (2001) as well as the cases with iso-elastic demand.

The numerical method used in most of the simulations with feedback strategies in this chapter is similar to the approach applied in Salo and Tahvonen (2001). This method is based on policy iteration in a discrete time, discrete space value function approximation and interpolation of value function. This is a relatively simple framework that can be adjusted to account for various functional forms of demand and costs. The computation time to find the equilibrium by this method, however, could be large. To improve the computation time, for example with finer resolution of state space, the collocation method, used by Miranda and Fackler (2002) to solve a number of dynamic optimization problems, could be applied. In this method, the infinite dimensional functional equation or the Bellman equation is replaced with a finite dimensional root-finding problem.

The present work is, to the best of my knowledge, the first study that applies this method to solve the problem of exhaustible resource oligopolies. Regarding the open loop equilibrium, no study in the dynamic game of exhaustible resources, to the best of my knowledge, has applied a numerical solution. The algorithm proposed in this paper is based on considering the problem in a discrete and finite time horizon and policy iterations for each producer given the extraction rates of the other producers.

For exhaustible resources such as oil and natural gas, there might be a significant difference in extraction costs across resource owners. The numerical approaches described in this chapter allow for more flexibility in terms of functional forms of producers' costs. To further extend the analysis under economic depletion, I repeat my initial simulations to derive a feedback equilibrium assuming higher production costs for one of the producers at any reserve level and obtain the phase diagrams for the relative share of produces.

Using the method based on policy iteration and value function interpolation to find the feedback equilibrium, I extend the results of Benchekroun and Van Long (2006) on the effect of resource discovery on the profit of non-identical resource producers. Benchekroun and Van Long (2006) analytically derive the conditions under which the profit of larger firms might decrease as resource level increases uniformly for all firms. My results in this part are similar to the findings of Benchekroun and Van Long (2006) that, with a more elastic demand, it is more plausible that the profit of some firms reduces with an increase in resource stock. However, the numerical analysis in this part shows that, with non-zero costs, the decrease in profit, caused by adding more resources, depends on the relative costs of production rather than the relative initial reserve of producers.

Chapter 1

The effect of transient variations in air pollution on individuals' life satisfaction: Evidence from Canada

1.1 Introduction

In mainstream economics, preferences for different goods are 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, 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 the revealed preferences in the markets for substitute or a complement private goods for that public good.

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. It is usually claimed 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. In this method, the revealed preference over a specific location, which is shown by the different housing prices of properties with an unequal amount of an environmental good, reflects the value of that environmental good. Thus, 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 economic theory. Utility is a representation of preferences and 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 individual experience at any moment. Over the last two decades, a developing stream in economics try to revive this subjective approach to utility which focus on 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 subjective measures of well-being on the part of economists. SWB data have been used by economics to investigate both macro and micro oriented subjects mostly through large empirical analyses of determinants of well-being in different countries (see Frey and Stutzer (2002); Di Tella and MacCulloch (2006) for survey of economic studies on SWB measures).

The subjective measures of well-being also have provided economists with a novel approach for the valuation of public goods which has always been a challenging subject in economics.

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.

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 offer 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 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. This concept of utility is different from what utility means often in modern economics which is based on individuals' preference revealed by their choices. We later discuss different utility concepts which provide different bases for the valuation of air quality.

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

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

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

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.

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.

The current study

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 assumptions underlying the use of this method have not been adequately discussed in the other studies using LS data for the valuation of a public good. We first explain the relation 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 chapter 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 ratio of compensating differential to annual income 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 in the chapter.

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 part of this chapter, 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.

The present chapter continues in section 2 by clarifying some the theoretical background underlying the use of life satisfaction data 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 relation between subjective well-being measures and the concept of utility in the literature of modern economics. Next, we focus on the LSA to derive the willingness to pay by individuals for improvement in air quality.

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 short run and long run. Finally, some of the advantages of the LSA over hedonic pricing and contingent valuation methods are briefly explained.

We continue with the explanation of the data sets and our empirical analysis in section 3. Section 4 includes the results of different estimations and the discussion of the results. 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 5 concludes the chapter.

1.2 The life satisfaction approach: conceptual basis

This section starts with a review of different interpretations of the term utility in its history in economic literature. In modern economics, utility is a set of preferences which explains an individual's choices. This concept of utility is known as decision utility (Kahneman, 2000).

However, in its earliest conception utility has been defined as a flow of pleasure and pain experienced by people at a given time. This interpretation of utility was introduced by Bentham (1789) and was used by 19th-century economists. 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.

Next, we explain the LSA as a non-market valuation technique for public goods valuation. The LSA is based on the estimation of the impact of a range of socioeconomic and environmental attributes of individuals on their LS as a measure of their experienced utility. We explain why LS is 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. 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. We then discuss some of the concerns regarding the time dimension for LS as well as its covariates, particularly income and air pollution—the environmental good of interest in the present study. Following the clarification of the assumptions underlying the LSA, we explain this approach in detail. Finally, we briefly explain the difference between LS and affect balance as a SWB measure based on momentary feelings and emotions.

Different utility concepts and their implication for environmental goods valuation

The concept of utility has been associated with two different approaches to determine the quality of life in its history. The first approach is based on the satisfaction of preferences within resource constraints. In this approach, utility is inferred from observed choices, meaning that individuals' choices provide all the information needed to infer their utility. Individuals are assumed to be rational maximizers of their own interests who have consistent preferences and can predict how they value different outcomes. This concept of utility, which is one of the bases of modern economics, is known as wantability, decision utility or choice utility (Kahneman, 2000).

Another approach to utility or the quality of life is based on what people experience as a good life. In its original interpretation, which is close to the ideas of Bentham (1789), utility is interpreted in terms of feelings of pleasure and pain or judgments about life. In this approach, it is assumed that people have a high quality of life if they perceive or experience their life to be good. This approach to life quality is mostly related to what is conceived as welfare in behavioral science. In this older interpretation of utility, whether people choose the options that they most enjoy is an open question, while in modern decision theory individuals are assumed to be rational utility-maximizers and their utility is represented by their choices. This conception of utility is called experienced utility (Frey et al., 2003; Kahneman, 2000) or normative utility (Beshears et al., 2008). Experienced utility, which is based on judgments of satisfaction and pleasure, can be empirically captured by self-reported measures of SWB such as LS.

These two different utility concepts provide distinct approaches for the valuation of environmental goods. Decision utility cannot be used directly to obtain individuals' preferences for environmental goods as they are public goods which are not chosen or traded in the market. However, decision utility underlies the methods based on either revealed preferences or stated preferences approach for environmental goods valuation. For example, the hedonic pricing method used to estimate the economic value of a local amenity such as an environmental good assumes that individuals maximize their decision utility by choosing their living location, with a level of local amenity (q) and other residential characteristics (x) and their consumption of a composite good (c) given the budget constraint. A simple framework to model this problem is the following:

$$\max_{c,x,q} U(c,x,q) \; s.t. \; c + r(x,q) = w$$

In the hedonic method, people trade off local amenities against wages (w) and rents (r). The marginal willingness to pay for local amenities such as air quality will be the income change that would compensate an individual for a marginal change in that amenity. This marginal willingness to pay would be an implicit price for the local amenity and under the above assumption it can be shown that it depends on the marginal impact of local amenity on rents ($\frac{\partial r}{\partial q}$) and wages ($w$). In practice, empirical studies using the hedonic approach estimate the impacts of various property characteristics including the level of environmental good on the property price and derive the marginal willingness to pay for the environmental good from the estimated coefficients. More complicated hedonic models account for forward-looking behavior of individuals in making location decisions using a dynamic framework in which people choose their location in different periods in order to maximize aggregate future utilities (Bishop, 2008).

During the last decades, however, there have been some concerns that revealed preferences are not a good guide of individuals' well-being. The rationality assumption underlying decision utility has been called into question by behavioral economists. The studies on anomalies in decision making started with the well-known works of Allais (1953) and Ellsberg (1961) who showed inconsistency in individuals' preferences. Kahneman (1994) reviews the literature from behavioral economics and psychology, which shows that people deviate from the assumptions of rationality in different ways such as making inconsistent choices, failing to learn from experience, and being reluctant to trade. If individuals have bounded rationality when they maximize (decision) utility, their observable choices do not necessarily reflect what maximizes their well-being. Thus, for the valuation of public goods, the exclusive reliance on the methods based on decision utility is open to doubt and restricts our understanding about what affects individuals' well-being.

A type of utility anomaly, which is relevant to public goods valuation, challenges the question of whether what people choose maximizes the hedonic experience associated with the consequences of choices. In fact, economic agents need to be able to predict the psychological or hedonic outcome of their decisions in order to choose the goods that they most enjoy when they are consumed. One important finding of behavioral economists is that individuals might not be able to predict the hedonic outcome of potential choices. For example, a very hungry shopper who is doing her weekly shopping might be induced by her current state of hunger to buy larger meal portions for her future consumption (Kahneman and Thaler, 2006). The misprediction of future utilities is more likely while making complex decisions with long-term trade-offs (Camerer et al., 2005). In essence, people do not always know what they will like and make systematic errors in predicting the hedonic outcomes of different choices (Kahneman and Thaler, 2006). For a review of the empirical literature on this subject, see Kahneman and Thaler (2006). Aside from the conceptual problems related to the rationality assumption, there exist some other concerns regarding the validity of the hedonic method and contingent valuation method — two well-known methods based on decision utility. A number of these problems will be discussed later in this section.

In order to add new insights to the propositions based on the objective position of conventional economic theory, economists have considered alternative ways to think about individuals' well-being. A developing approach in recent economic literature has been to revive the Benthamic interpretation of utility as the experience of pleasure and pain or experienced utility. People are assumed to be the best judges of their life quality and are able to report how favorable they find their life quality by choosing a level from a particular scale. This directly measurable flow of (experienced) utility reflects individuals' well-being at the time of reporting their score. This notion of utility provides a more direct approach to individuals' welfare which could be used alongside conventional welfare analysis, which is based on decision utility.

The self-reported judgments of satisfaction and pleasure are empirically captured by the measures of SWB. These measures have been applied in psychological studies for a long time. For the reviews of empirical studies of SWB in psychology, see Kahneman et al. (1999); Diener et al. (1999). According to Frey et al. (2010), SWB is considered the umbrella term for different self-reported measures distinguished along judgmental and emotional dimensions. The emotional reactions, mood, and feelings a person has are referred to as affect. Life satisfaction (LS), on the other hand, is mainly a measure of cognitive judgments about one's life as a whole, but it also reflects, to some extent, transitory feelings and emotions.

Reports of SWB can have a useful role in economics subject to the caveats associated with subjective measures. Over the last two decades, there has been growing interest on the part of economists in using SWB data. They have especially contributed large scale empirical analyses to gain insight into the impact of different potential factors on well-being. These factors consist of a range of individuals' personal, economic and social attributes as well as wider economic and environmental factors affecting life quality. The economic studies investigating SWB data mostly rely on LS as a measure for well-being. Economists have applied LS data to find the well-being impacts from economic variables such as income, relative income, unemployment, and inflation as well as institutional factors such as the type of democracy and the extent of government decentralization. For surveys of economic studies related to LS see Frey and Stutzer (2002); Dolan et al. (2008).

As a significant application, reports of LS have been used to derive a new non-market valuation for environmental goods. The life satisfaction approach (LSA) makes use of LS data as a measure for experienced utility along with a range of factors affecting well-being. In essence, this method is based on estimating the impact of different determinants of well-being including income and the environmental good being valuated on LS. The implicit willingness to pay for the environmental good is then calculated using the marginal impact of income and the environmental good on LS. The LSA has been applied by economists to obtain the value of a number of environmental goods such as climate (Frijters and Van Praag, 1998), flood

(Luechinger and Raschky, 2009), and air quality (Welsch, 2002; Luechinger, 2009; Levinson, 2012).

Using experienced measures of well-being can refute a number of problems that anomalies cause for the approaches based on decision utility. For example, the systematic errors in predicting hedonic outcome of choices is not relevant as SWB measures emphasize *ex post* judgments of experience. Empirical studies of SWB data help researchers verify the underlying assumptions of conventional techniques such as hedonic pricing. For example, the negative impact of air pollution on LS in the LSA shows that, contrary to what is assumed in hedonic method, air pollution is not completely capitalized in the housing market (Frey et al., 2010).

The rationale behind using LS for environmental goods valuation

Most of the studies related to SWB in economics have used representative and large-scale sampling of LS evaluation. Although LS is mainly a measure of cognitive judgment about life quality, different studies show that it is indeed a combination of cognitive judgments and affective states (Frey et al., 2010; Schwarz and Strack, 1991). This type of experience-based and affect-contaminated cognition is close to the theory of Sumner (1996) on the nature of welfare in philosophy[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 subjective well-being (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 inter-personally comparable; and (6) be available at a sufficiently large scale. The study of Frey

[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).

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 (stock of) 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, 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.

Finally, it is worth mentioning that LS and affect, as two different measures of SWB, reflect different aspects of individuals' well-being. Although these measures are positively correlated and both reflect experienced utility at the time of the interview, LS reflects a type of respondents' experience which is distinct from what is captured by net affect. While affect is a measure for positive and negative feelings and emotions at the time of the interview, LS reflects how people think about overall quality of life rather than merely their momentary feelings.

According to Frey et al. (2010), in order for any of these two measures to represent individuals' welfare, one important assumption is necessary: the standards used by individuals to report well-being scores should be similar to the standards they would like to pursue in realizing their ideal of the good life. Some people might see their well-being in moment-to-moment (positive) emotions. For these people, welfare could be best captured by the measures of affect captured by methods such as Experienced Sampling Method (ESM). For some other individuals, life quality or well-being depends on both current feelings and an experience of life which is more general than momentary emotions. In this case, LS will be a better subjective measure of welfare.

As mentioned earlier, economic studies using SWB data mostly rely on the reports of LS as this measure is sensitive to both stable characteristics of individuals as well as to the momentary aspects of their life. Additionally, LS scores show stability over time more than the scores for affect measures (Diener, 1984). This makes LS an appropriate measure of well-being for policy analysis and long-term decisions. Higher stability of LS scores over time compared to affect measures can be better understood by identifying the different variables predicting these two measures. The analysis of Kahneman and Krueger (2006) shows that demographic factors such as income, education, and marital status predict LS more strongly than they predict affect. These variables have a pretty stable level over time. On the other hand, time use, which is more volatile, predicts net affect more than it predicts LS.

The life satisfaction function and willingness to pay for environmental goods

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 valuated (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.

Temporal dimension of LS

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 question where this experience is affected by a range of factors. In fact, they do not report a combination or summation of how they have experienced their life in different periods in the past.

The mentioned cognitive judgment framework behind LS scores also implies that experienced utility captured by LS is not a measure for the summation (stock) of future utilities, which is the objective function maximized in standard economic theory. Thinking about the future might have some impacts on LS evaluation, but LS is mainly an ex-post measure of well-being.

Since LS is a flow of experienced utility, the relation between this measure and its determinants is modeled by the above-mentioned simple mathematical framework, which involves no integration over time or discounting. How favorable the life experienced at the interview time can be explained by different factors affecting satisfaction at that time. In fact, all economic studies investigating LS data have used this simple framework to estimate the relation between LS and the satisfaction covariates that affect respondents at the time of the interview. Obviously, many of these covariates are fairly stable for a given individual over time.

Temporal dimension of the LS determinants

Now the question is how can LS be a measure of global judgment about life if it represents individuals' utility at a given time? The determinants of LS are the key to answering this question. These determinants consist of a number of fairly stable personal and socioeconomic attributes including social background, personality traits, and social network that have been formed during one's lifetime as well as the recent change in life circumstances affecting well-being. Headey and Wearing (1991) suggest two economically familiar terms of stock and flow variables for different determinants of satisfaction. They consider stable social and personal characteristics as stock variables. On the other hand, transitory life events can be thought of as flow variables that affect LS. When reporting a LS score, the personal and social characteristics of individuals which were formed throughout their life as well as stable attributes of their environment affect experienced utility as a measure of current well-being. The impact from these stock variables explains why the reports of LS, which represent a flow of utility, reflect people's evaluation of their life as a whole. These rather stable characteristics also justify the moderate stability of LS for an 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 fact, the first study using SWB data in economics is by Easterlin (1974), who shows that, although richer people are, on average, happier, increasing the income of all people does not change the happiness of all. In essence, the empirical literature on this subject indicates that people with higher income report, on average, higher scores of SWB, but income increases well-being at a diminishing rate. 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.

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.

The LSA and other approaches to environmental goods valuation

Valuation of air quality using a well-being measure such as LS has a number of advantages over the hedonic method. In the seminal work of Rosen (1974) on hedonic model, in order to derive MWP from the hedonic regression coefficients, the housing market needs to be in equilibrium. In reality, the equilibrium condition is unlikely to hold and the estimated coefficients should be interpreted with discretion (Coulson and Zabel, 2013). The price difference between two equal houses with different level of an amenity does not necessarily reflect the willingness to pay for the amenity when the market is not in equilibrium. It is usually claimed that the hedonic method underestimates the negative effects of air quality (Frey et al., 2010). One reason for this underestimation is that, with costly migration, the benefits of clean air are incompletely reflected in housing prices. The LSA, on the other hand, is not dependent to equilibrium condition.

Another reason is that the behavior of individuals in the private market is a function of their perceived and not actual risk of being in bad air quality. If the perceived risk of pollution is different from the actual risk, due to the lack of adequate information, a house buyer or renter might underestimate or overestimate the value of air quality. The problem of distorted risk perceptions is of less importance in the LSA as this approach evaluates the willingness to pay for a given public good based on current condition of individuals (Frey et al., 2010). In fact, a person's well-being is affected by air pollution through health impacts or other mentioned channels even if she does not notice a high pollution level. So, the LS evaluation is independent, to a great extent, from individuals' perception or their information about the risks of being exposed to bad air quality. Finally, it is worth noting that the LSA can be considered as a way to verify the assumptions underlying methods based on decision utility. For example, the negative impact of air pollution in the LSA literature admits that air pollution is not completely capitalized into the housing market.

The preferable property of the LSA over contingent valuation methods is that the questions asked in the LSA have no hypothetical form, unlike those in the contingent valuation method. The hypothetical nature of the questions in the contingent valuation method results in superficial answers and a symbolic valuation of public goods (Kahneman et al., 1999). In contrast, individuals have no incentive to give strategic responses to the LS questions (Benjamin et al., 2012), since the connection between LS and air quality is made ex-post by the researchers. In fact, the respondents may not even consciously know that they value environmental quality while expressing their satisfaction with life.

1.3 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.

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. The hourly concentration data for a number of pollutants 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.

The emission of most of the air pollutants in Canada had a decreasing rate during the last decays. Since 1990, the emission of SO_2, NO_2, and CO has decreased by approximately 60%, 30%, and 60% accordingly. For fine particular matter ($PM_{2.5}$) , however, the pollution level is currently 5% higher than 1990 level. Table 1.1 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).

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, they will self select the locations with house price and air quality levels that give them more utility. In a hypothetical case of perfect 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 Chay and Greenstone (2005), 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.

In the LSA, the relation between LS and its determinants is estimated by the following equation: $\mu g\, m^{-3}$

$$\mathrm{LS}_{it} = \alpha \log Y_{it} + \beta \mathrm{pol}_{it} + X_{it}\gamma + \lambda_{it} + y_t + m_t + \epsilon_{it} \tag{1.1}$$

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.

To obtain the marginal rate of substitution between income and pollution, we apply the

Table 1.1: 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 $_{2.5(\mu g\, m^{-3})}$	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.

condition $dLS_{it} = 0$. Assuming no change in all the variables other than income and pollution, 1.1 gives

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

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 (1.1), 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 later in this chapter, 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.

1.4 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 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.

[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.

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 1.2 reports the different estimations of equation (1.1). The model estimated in column 1 of Table 1.2 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. 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 2.2. 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 1.2: The effect of pollution on LS

Dependent variable	LS	LS	LS	LS	LS
SO_2 24 hrs. (ppb)	-0.0011	-0.0024	-0.0025	-0.0028	-0.0052*
	(-0.6)	(-1.18)	(-1.352)	(-1.438)	(-1.972)
$\overline{SO_2}$ by station and month (ppb)		0.0042			
		(1.048)			
ln (household income)	0.203***	0.203***	0.213***	0.173***	0.173***

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

	(29.10)	(29.67)	(32.44)	(21.89)	(22.70)
female				0.049***	0.055***
				(6.23)	(5.45)
Age				-0.027***	-0.027***
				(-12.870)	(-9.822)
Age squared				0.00028***	0.00027***
				(11.96)	(9.665)
Married				0.152***	0.143***
				(8.802)	(6.879)
Common law				0.119***	0.101***
				(6.339)	(4.120)
Widowed				0.024	0.035
				(1.454)	(1.475)
Separated				-0.062**	-0.095**
				(-2.112)	(-2.315)
Divorced				-0.036	-0.003
				(-1.489)	(-0.097)
At work last week				0.100***	0.070**
				(3.809)	(2.171)
Absent from work last week				0.115***	0.165***
				(3.313)	(3.780)
No job last week				0.069***	0.042
				(2.977)	(1.392)
Permanently unable to work				-0.361***	-0.358***
				(-8.121)	(-6.310)
Secondary graduate				0.060***	0.057*
				(2.954)	(1.816)
Some post secondary				0.091***	0.092***
				(3.946)	(3.605)
Post secondary graduate				0.086***	0.102***
				(3.846)	(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***	2.014***	2.052***	2.733	2.733
	(25.21)	(26.31)	(25.05)	(27.84)	(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
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.
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 1.2, three alternative specifications are considered. The results are reported in Table 1.3. Column 1 in Table 1.3 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 1.2. 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 2.2. 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 1.4 estimates the same specification as the one in column 5 of Table 1.2 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.

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 1.1. 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

Table 1.3: 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
R-squared	0.074	0.094	
N	34587	34587	34587

See the footnotes to Table 1.2.

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. Finally, it is worth to mention that for measuring very local and spatially-variating pollutants such as CO and NO_2, portable air monitoring sensors are more accurate compared to the fixed monitoring stations.

For particulate matter ($PM_{2.5}$), referring to Table 1.1, 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 1.4, 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 1.4 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 1.5 contains a quadratic in SO_2 levels. The coefficient of

Table 1.4: 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. ($\mu g\, m^{-3}$)			-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
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 1.2.

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 1.5 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 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 1.2.

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 1.6 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

Table 1.5: 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
R-squared	0.088	0.14[b]	0.088
N	34587	34587	34587

See the footnotes to Table 1.2.
[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).

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.

Table 1.6: 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* (-1.815)	-0.023* (-2.055)
ln (household income)	0.165*** (22.31)	0.141 (1.591)
Weather variable		
Mean temperature (°C)	-1.5e-5 (-0.0093)	-0.010 (-1.224)
Temperature difference (°C)	0.0012 (0.522)	-0.0176 (-1.217)
Rain (mm)	-0.0015 (-1.435)	-0.019** (-2.288)
Snow (cm)	-0.0027 (-0.741)	-0.0022 (-0.074)
Cloud cover	0.0128 (0.732)	-0.0965 (-1.090)
Constant	2.730*** (19.55)	3.266*** (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
R-squared	0.087	0.276
N	33699	888

See the footnotes to Table 1.2.

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 1.7 contains the estimations of the baseline model (column 5 of Table 1.2), 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 1.7, there is no statistically significant effect of SO_2 concentration on any of these satisfaction measures.

1.5 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

Table 1.7: 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
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 1.2.

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 earlier in this chapter, 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 in which we conducted all the analyses in the chapter.

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 1.8 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,

[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.).

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 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 1.8: 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

1.6 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 individuals' welfare. A number of studies try to estimate this impact on individuals' welfare from an economic point of view. Among all the methods addressed in the literature, there is a growing interest in the life satisfaction approach (LSA) as a non-market valuation method. 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 chapter we show 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, the results of this chapter indicate 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.

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 chapter 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 1.9: Corelation of SO_2 with weather variables

	SO_2	Rain	Snow	$T_{dif.}$	T_{mean}	Cloud cover
SO_2	1					
Rain	-0.071	1				
Snow	0.013	-0.026	1			
$T_{dif.}$	0.053	-0.219	-0.128	1		
T_{mean}	-0.022	0.137	-0.252	0.199	1	
Cloud cover	-0.026	0.245	0.165	-0.383	-0.055	1

Table 1.10: 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

Chapter 2

The impact of daily weather conditions on life satisfaction: Evidence from Canadian cross-sectional and panel data

2.1 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 for many years and have investigated their causes, correlates, and outcomes (Schwarz and Strack, 1991; Kahneman et al., 2003). In general, subjective well-being 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). Life satisfaction relies on individuals' own evaluations of their continuing life circumstances. 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. In essence, 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 by individuals of non-market goods such as environmental goods. Researchers have used the life satisfaction approach 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).

The impact of weather on individuals' 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 a measure 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.

Although LS is mainly a measure to capture the cognitive and evaluative aspects of well-being, the judgments of well-being measured by LS also are sensitive to some extent, on 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 . From the psychological point of view, the reason for the impact from recent events is that evaluating general life satisfaction requires people to have a judgment about different aspects of their life and then integrate those judgment into a single number. The complexity of this task might lead the respondent to rely her judgment in part on some recent life events such as her mood at the time of the interview (Schwarz and Strack, 1991). A number of empirical studies show the impact of some recent events such as spending time in a pleasant rather than an unpleasant room or when one's favorite team wins a game on the reported values of LS(Schwarz et al., 1987).

Schwarz and Strack (1991) explain how individuals' moods at the time of judgment about satisfaction affect what they report. 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.

The scores of LS depend, to a great extent, on individuals' personal and socioeconomic attributes as well as the characteristics of their environment. A number of predictors of LS are age, sex, marital status, level of education and employment status of respondents. As 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). In summary, LS scores demonstrate relative stability and are sensitive to temporal conditions at the same time. So LS can be used to capture the well-being impacts from both long-term local climate, as a stable environmental condition, and weather as a rather transitory condition.

It should be noted that although mood variability affects the reporting of satisfaction with life, in general it does not have an aimpact 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 the 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 life satisfaction. 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 affect. 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 shocks. 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.

If weather variables have a significant effect on LS, accounting for them is important when evaluating the effect of the LS determinants correlated with weather. For example, in the study of air pollution's impact on LS, considering weather variables in the right-hand side of regressions is of great importance since weather is strongly correlated with air pollution. All the studies on this subject such as Luechinger (2009, 2010), Levinson (2012), and Barrington-Leigh and Behzadnejad (2015) include weather variables in their models.

Studies on the relation of life satisfaction to 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. 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. 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.

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. 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.

The current study

In this study, we look at the impact of daily variations in weather conditions on reported LS using the 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 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 increases by approximately 0.01 on a five-point scale. 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.

Finally, 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 is needed to test for the direct impact of climate on LS.

The chapter 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. The results of different estimations along with the discussion of the results are presented in section 3. Section 4 concludes the chapter.

2.2 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. 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.

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.

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 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 month-station 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 month-station algorithm compared to the nearest station algorithm. However, it should be noted that the relative number of missed observations resulted from the month-station 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 chapter, 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.

2.3 Results

Table 2.1 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.

Table 2.1: 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.

The first six columns show the estimated coefficients of the models with only daily rain or 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 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 2.2 includes the same specifications as those in Table 2.1, but controls for location fixed effects using a set of dummies for all the weather stations. Similar to Table 2.1, 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.

To control for the seasonal variations in LS, month fixed effects should also be considered in

Table 2.2: 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 2.1.

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 month-station combination of the respondents' locations and interview dates are considered. In addition, the individuals are clustered into month-station groups using the algorithm explained in detail in the data section. Tables 2.3 and A.3 report the results of the estimation of the model with month-station fixed effects and clustering. As can be seen in column 1 of Table 2.3, 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 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 2.4. Columns (1-3) and (10-12) of Table 2.4 are identical to columns (1-3) and (7-9) of Table 2.3 except that they also show the coefficients of all the socioeconomic variables not displayed in Table 2.3.

Compared to some of the major determinants of LS, the marginal effect of the weather variables on LS is small. 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

Table 2.3: 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 2.1.

of LS. Columns (4-6) of Table 2.4 include only weather variables. In contrast, columns (7-9) 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 2.4: 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

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
	(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)
cloud				0.0039	0.012	0.031*				0.0030	0.014	0.025
				(0.53)	(0.67)	(1.7)				(0.41)	(0.80)	(1.4)
cloud (7 days)				-0.0039	0.023	0.043				-0.0019	0.028	0.050
				(-0.28)	(0.73)	(1.4)				(-0.14)	(0.89)	(1.56)
Constant	2.78***	3.55***	2.27***	4.31***	4.30***	4.21***	2.81***	3.45***	2.45***	2.80***	3.51***	2.15***
	(42.2)	(11.4)	(11.4)	(202.)	(23.0)	(46.2)	(53.6)	(13.1)	(14.0)	(37.1)	(10.8)	(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	1048811835	11835	131553	111249841	11124	206859	1588014073	15880	131553	984111124	11124
R^2	0.089	0.070706	.123	0.016	0.065709	0.058	0.091	0.686067	0.121	0.089	0.712076	0.126

See the footnotes to Table 2.1.

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).

Table 2.5 presents results from the estimation of some alternative models. All the specifications control for year and month-station fixed effects as well as for all the demographic and socioeconomic variables considered in Table 2.3. 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 2.5, 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 3 of Table 2.5, 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 the last column of

Table 2.5, daily rain is again the only weather variable with a significant effect on LS in the ordered probit model.

Table 2.5: 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 2.1.

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 separately. 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 2.6 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 2.6, 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. 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.

One channel through which temporal variations of weather might have an impact on well-being is by affecting individual's health. 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 2.7 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

Table 2.6: 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 2.1.

Table 2.7: 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 2.1.

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 2.3. 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 2.7, the effect of daily rain and cloud is higher and statistically significant for the poor health category.

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 well-defined (Schwarz and Strack, 1991). 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 2.8 shows the results of the estimation of our preferred model (column 7 of Table 2.3) using the measures of satisfaction with health, job, leisure, friends, neighborhood, financial situation, and housing. From the total of 42 estimated weather coefficients, six coefficients are significant at 10% level. The ratio of the significant variables to total number of variables is approximately equal to the ratio that would be randomly expected. The statistically significant variable is different for each of the satisfaction measures. In general, Table 2.8 constitutes evidence consistent with the idea that domain-specific satisfactions are less prone to be affected by transient factors such as weather.

Table 2.8: 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 2.1.

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 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 2.9 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. [1].

In columns (1-8) we look at the effect of climate on LS. 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 has 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.

[1] While the change in climate is negligible within the areas close to each monitoring station, climate variations exist within each province.

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 the columns with odd numbers, in the CCHS sample a number of long-term climate variables have a significant impact on LS. However, there is almost no impact of climate on LS when individual fixed effects are controlled in the NPHS sample.

As can be seen in Table 2.9, the set of climate coefficients that are significant is larger in the estimations with the CCHS compared to the NPHS with individual fixed effects. Nevertheless, we cannot reject the hypothesis that the coefficient of a given variables in the NPHS is equal to the similar coefficient in the CCHS. 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. Feddersen et al. (2012) further interpret this result as evidence for no direct effect of climate on LS. They suggest that rather than climate increasing satisfaction with life, more satisfied people are living in or being attracted by certain climates. In other words, some characteristics of individuals, which are omitted in cross-sectional analysis, make people with higher satisfaction prefer some specific locations.

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.

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. In accordance with the specifications containing station-month fixed effects, daily rainfall has a significant impact on LS in the CCHS sample. The rain coefficient in the NPHS is similar to that in the CCHS, but is not statistically significant. The rain coefficients are similar to what was obtained in Table 2.4 with station-month fixed effects. [2]

[2] In the hedonic model, assuming no impact of amenity on production costs, wages are higher if amenity is positively correlated with welfare and vice versa. So, in the specification without income, we expect for the climate variables that are negatively correlated with LS (such as rain or temperature difference) to have a higher (less negative) coefficient and for the variables positively correlated with LS to have a smaller coefficient. I repeated the climate table without income, but I didn't get the expected result for most of the coefficients.

Table 2.9: Climate and life satisfaction

Year: $T_{mean}(^{\circ}C)$	-0.0043***	-0.0039	-0.0042***	-0.0048	-0.0035***	-0.0066				
	(-3.6)	(-0.37)	(-3.4)	(-0.67)	(-2.7)	(-0.86)				
Year: $T_{max}\_T_{min}(^{\circ}C)$	0.0093***	-0.014	0.0096***	-0.036**	0.0030	-0.039**				
	(4.1)	(-0.66)	(4.1)	(-2.5)	(1.1)	(-2.4)				
Year: Days sunny	-0.0002	0.0000	-0.0002	0.0002	-0.0005***	0.0003				
	(-1.18)	(0.010)	(-1.1)	(0.38)	(-3.6)	(0.20)				
Month: T_{mean}			0.0008	-0.0018			-0.0006	-0.0007		
			(0.48)	(-0.42)			(-0.27)	(-0.13)		
Month: days sun			-0.0002	0.0067			-0.0034**	0.0024		
			(-0.16)	(1.1)			(-2.0)	(0.34)		
Month: days snow			0.0007	-0.0019			0.0004	-0.0020		
			(0.86)	(-1.1)			(0.5)	(-1.1)		
Month: days rain			0.0007	0.0050			0.0007	0.0079*		
			(0.37)	(1.3)			(0.29)	(1.7)		
log (HH income)	0.161***	0.0936***	0.161***	0.0864***	0.161***	0.0837***	0.161***	0.0804***	0.163***	0.0946***
	(30.8)	(2.71)	(30.6)	(4.78)	(29.4)	(4.81)	(29.6)	(4.60)	(25.5)	(4.84)
Day: T_{mean}					-0.0001	0.0021	-0.0003	0.0004	-0.0006	0.0010
					(-0.10)	(0.71)	(-0.15)	(0.10)	(-0.38)	(0.26)
Day: T_{max}-T_{min}					0.011***	0.0040	0.013***	0.0001	0.016***	0.0096
					(4.4)	(0.45)	(5.5)	(0.008)	(5.0)	(0.86)
Day: precipitation					0.0007	-0.0001	0.0006	-0.0015	0.0015***	0.0010
					(1.4)	(-0.078)	(0.93)	(-0.84)	(2.7)	(0.57)
T_{mean}									-0.0009	0.0009
									(-1.1)	(0.54)
$T_{max}\_T_{min}$									-0.0007	-0.0049*
									(-0.51)	(-1.69)
rain (mm)									-0.0014**	-0.0014
									(-2.5)	(-1.3)
snow (cm)									-0.0015	0.0043
									(-0.92)	(0.92)
cloud									0.0017	-0.0068
									(0.22)	(-0.35)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS
cloud (7 days)									0.0018	0.0006
									(0.14)	(0.017)
Constant	3.07***	3.99***	3.06***	3.91***	3.06***	4.11***	2.98***	3.92***	2.8270***	3.9040***
	(35.9)	(7.14)	(31.9)	(10.6)	(32.0)	(8.42)	(27.7)	(12.1)	(23.4)	(11.5)
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	CCHS	NPHS	CCHS	NPHS	CCHS	NPHS	CCHS	NPHS	CCHS	NPHS
Observations	195732	2466	195010	15327	180395	14641	180387	14638	128456	10648
R^2	0.077	0.721	0.077	0.658	0.078	0.656	0.078	0.655	0.078	0.686

See the footnotes to Table 2.1

2.4 Conclusion

The use of subjective measures of well-being, 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, studying the reliability of these measures and finding the source of different biases in reporting them are ongoing tasks.

Individuals' moodat 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 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 chapter we aim to 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 marginal effect of day-to-day variations in rainfall is similar to the effect of 1% change in household income. While a 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.

A number of long-term climate attributes are shown to affect LS in our cross-sectional sample. However, with individual fixed effects only a small set of climate variables is found to be significant. This suggests that the direct impact of climate on LS might be very small and individuals are clustering into certain locations depending on some omitted characteristics correlated with both LS and the choice of living location. Further analysis on large panel data sets can help to find whether the direction of causation is from 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 a panel data set to support the widely used repeated cross-sectional data sets such as the Gallup World Poll can address weather bias to some extent.

2.5 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 2.1.

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

Variables	Obs.	Mean	Std. Dev.
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
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	0.51	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	173635	7.22	10.74
Temperature difference	173635	9.78	4.32
Rain	140903	2.25	5.97
Snow	141662	0.47	2.11
Cloud cover	165807	1.10	0.69
Cloud cover (7 days)	181485	1.18	0.47
Year: T_{mean}	206854	6.45	3.08
Year: $T_{max}\_T_{min}$	208800	9.68	1.50
Year: days sun	194456	295.15	28.96
Month: T_{mean}	206846	6.63	9.95
Month: days sun	193738	25.09	3.86

Variables	Obs.	Mean	Std. Dev.
Month: days snow	206832	5.69	9.47
Month: days precipitation	206846	4.72	2.33
Day: T_{mean}	191575	6.39	9.94
Day: T_{max}-T_{min}	191575	9.77	2.29

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

Variables	Obs.	Mean	Std. Dev.
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	13790	8.21	11.44
Temperature difference	13790	9.89	4.18
Rain	11835	2.33	6.19
Snow	11888	0.41	1.90
Cloud cover	13268	1.08	0.68
Cloud cover (7 days)	14321	1.16	0.46
Year: T_{mean}	15880	6.43	2.93
Year: T_{max}_T_{min}	17950	9.81	1.50
Year: days sun	15424	296.04	26.71
Month: T_{mean}	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
Day: T_{mean}	16926	7.34	10.80
Day: T_{max}-T_{min}	16926	10.03	2.19
Day: precipitation	15222	41.68	9.64

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 2.1.

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 2.1.

Chapter 3

Oligopolistic competition in the non-renewable resource market

3.1 Introduction

Modeling the structure of the exhaustible resource market has been a challenging topic for many years. During the 1970s, resource scarcity and the availability of natural resources for future generations were the focus of studies in this area. In recent years, interest in non-renewable resources is due more to environmental concerns such as the effect of international carbon dioxide control on the oil market. There has been a large amount of literature on modeling the supply-side structure among the different aspects of this market. The earliest study that tries to formulate this aspect is the well-known work by Hotelling (1931). This study is also the first work that mentions the idea of oligopolistic competition in the exhaustible resource market. Although the analysis in Hotelling (1931) is based on comparing monopolistic market versus perfect competition, he suggests, though he does not explicitly show it, that oligopolistic competition is closer to reality.

The studies that analyze the exhaustible resource market supply within a dynamic game framework were developed after the formation of OPEC and the 1973 oil crisis. In general, these studies can be divided into the two broad categories of either common or non-common resources. The focus in the present work is on the latter category, in which each producer extracts its own resource but supplies on the same market as the others. Salant (1976) and Gilbert (1978) are the first studies with a dynamic game structure in modeling resource extraction. Salant (1976) derives the Nash-Cournot equilibrium in a cartel fringe framework that represents OPEC versus non-OPEC oil producers. Under assumptions of either zero or increasing marginal costs, the cartel formation increases the profit of non-members more than of the cartel. There are two phases of extraction, with both the cartel and the fringe extracting in the first phase. The cartel restricts its sales in the first phase so that it will be the monopoly in the second phase.

Gilbert (1978) develops a Stackelberg framework in the cartel-fringe competition, in which the cartel is the leader and the fringe is the follower. With constant costs for the competitive fringe, the cartel strategy in equilibrium is independent of its own costs and is only determined by fringe characteristics. In contrast, with capacity constraint, the cartel optimal policy is the same as that of a conventional limit-pricing monopoly. The problem with the open-loop equilibrium is that the attained policy may not be time consistent (Groot et al., 2003).

A number of studies have extended the analysis of the open-loop game of oligopolistic firms in different dimensions. Lewis and Schmalensee (1980) consider an oligopoly with a number of suppliers under assumptions of both equal and unequal costs. Assuming equal costs and constant total reserve, increasing the number of producers or equalizing their reserve will lead to more rapid resource use. In the presence of unequal costs, the path of extraction is not efficient; high cost firms may exhaust their reserve before low cost firms.

Loury (1986) considers a number of competing firms with equal costs but different reserve levels. Under a general demand function, the so-called "oil'igopoly" model predicts an increase in the degree of concentration with time. Thus, the resource will eventually be extracted by a monopoly. Another prediction of this model is that the producers with a greater reserve extract more, but the proportion of extraction to reserve is smaller than that of the producers with less reserve. These predictions have been shown to correspond to the reality of the oil market in an empirical study by Polasky (1992).

There is a special case in which each firm extracts the resource from its own property, but the resource could seep from one property to another. Khalatbari (1977) and Kemp and Long (1980) are among the studies that investigate this special case. As the amount of seepage increases, the problem will be closer to the one of the common property resource.

Benchekroun et al. (2009) consider two types of firms that differ in constant marginal extraction costs. Demand is linear and the firms belong to either the high or the low marginal cost type. The open-loop equilibrium policy implies that there is always a phase in which both low and high cost firms extract. From their oligopoly framework, they derive the cartel-fringe equilibrium. The high cost firms will have a price-taking behavior as their number goes to infinity. One important result of Benchekroun et al. (2009) is that if the low cost firms have a small cost advantage or a large aggregate stock, the more expensive resources are exhausted first. This will be a violation of Herfindahl's rule and thus is not desirable from the welfare maximization perspective.

The above-mentioned studies focus on the open-loop equilibrium in which each player determines its optimal strategy knowing the other players' paths of extraction. The equilibrium strategy is determined at the initial time, and the production path of each firm is only time dependent. The advantage of the open-loop equilibrium is that it is easier to derive analytically compared to the feedback equilibrium. Moreover, this is the only equilibrium that could be obtained with no information about the reserve level of the other players during the extraction period. In this equilibrium, if one of the players deviates from the optimal strategy, the strategies of the others will no longer be optimal. In reality, the producers might not be able to commit to the equilibrium strategy because of many reasons, such as an absence of property laws.

Since the assumption of precommitment by all players might not be valid in several circumstances, the alternative is to rely on the feedback equilibrium where possible. In this kind of equilibrium, the optimal policy of the firms will depend only on the state variable or all the firms' reserve level. For deriving the feedback equilibrium, future actions are considered to obtain current optimal decisions, and so the strategies in equilibrium are subgame perfect. The so-called Markov Perfect Nash Equilibrium (MPNE) is subgame perfect by construction (Dockner, 2000; Haurie et al., 2012).

There has been an increase in the number of economic studies using feedback strategies; see for example Long (2010) for a survey of studies using feedback strategies in economics. Finding the equilibrium strategies analytically, however, is more difficult in the feedback as compared to the open-loop case. In fact, the analytical solution exists only for a few special cases, such as iso-elastic demand combined with zero costs (e.g., Benchekroun and Van Long, 2006) and linear demand and linear unit costs under economic depletion (Salo and Tahvonen, 2001). Thus, to obtain the solution in the other cases, one should rely on a numerical solution. Salo and Tahvonen (2001) apply a numerical method to find the equilibrium strategy of the players with different functional forms of demand and costs. An important assumption in their work is the economic rather than physical depletion of the resource. In their model, unit costs depend negatively on the reserve level. There will be a certain resource level at which it is not beneficial to further extract the reserve.

Salo and Tahvonen (2001)'s main result contrasts with the finding of previous works, such as the "oil'igopoly" theory of Loury (1986), with fixed unit costs and physical depletion. Whereas in the "oil'igopoly" model high cost firms exit the market sooner, in this model they actually enter the market later. Therefore, instead of moving toward monopoly, the competition increases over time. Moreover, symmetric suppliers that differ only in initial reserve always approach a turnpike with equal shares. In the case of nonlinear unit costs, supply concentration initially increases as predicted by the "oil'igopoly" theorem, but the firms eventually move to equal share after some time. Salo and Tahvonen (2001) is, to the best of my knowledge, the only study that has examined a numerical method to find the feedback strategies for the problem of exhaustible resource oligopoly. In their paper, they use the Markov chain approximation of value function and iteration in the policy space to find the equilibrium.

All of the mentioned studies investigate the exhaustible resource problem in a deterministic environment. In the real world, uncertainties may exist due to long-term dynamic involved in resource production. The uncertainty could be attributed to either demand function or reserve level. The stochastic demand case has been studied by Zabel (1970) and Lewis (1977). Pindyck (1980) derives the equilibrium extraction for the monopolistic as well as the competitive market when there is uncertainty about the future values of demand and reserve. The uncertainty over the reserve stock has been studied by Pindyck (1978), Deshmukh and Pliska (1983), and Polasky (1992). Similar to stochastic demand, reserve uncertainty has been examined in either competitive or monopolistic markets.

The objective of the present paper is mainly to examine the robustness the results of the studies in the dynamic game of exhaustible resources that were limited to few cases with an analytical solution. In the first part of the paper, we focus on the dynamic game of resource producers under the assumption of economic depletion instead of physical depletion of resources. This assumption accounts for the fact that reserves are heterogeneous and that their complete physical depletion may not be possible. Starting by feedback strategies, the analysis in Salo and Tahvonen (2001) is extended to the case with iso-elasic demand together with reserve-dependent costs. It is shown that with iso-elastic demand, the relative share of the firm with a smaller reserve increases with time. This confirms the results of Salo and

Tahvonen (2001) with different functional forms of demand. The iso-elastic demand function will be used later in the paper to extend the analysis by Benchekroun and Van Long (2006) on the effect of increasing resources on producers' profit.

The majority of the studies that model dynamic game in the exhaustible resource market focus on the open-loop equilibrium. Following the analysis in the feedback case, we derive the open-loop equilibrium using a numerical approach for the same cases previously investigated. No study, to the best of my knowledge, has addressed a numerical algorithm to find the open-loop equilibrium in the exhaustible resource market. Subsequently, the phase diagrams and the time path of resource extraction in the open-loop equilibrium are compared with those of the feedback equilibrium.

To find the feedback equilibrium, we rely on two different methods. The first method is based on a discrete time, discrete space value function approximation. The policy and value function of all players can be reached by proper iterations in the policy function space. The interpolation of value function is a crucial part of this approach. Similar to the study of Salo and Tahvonen (2001), at each iteration we find the profit-maximizing policy in a number of predetermined reserve levels given the value functions obtained in the previous iteration. However, to find the value function at any level of reserve, we use the linear interpolation method rather than the more complicated approach of Markov chain approximation used in Salo and Tahvonen (2001). While this is a straightforward method to find the equilibrium strategies, it might be time-consuming especially when we use a finer resolution to discretize the state space.

To reduce the computation time in such cases, another method, namely the collocation method, might be an alternative. This method is based on replacing an infinite-dimension functional equation with a finite-dimension root-finding problem. The continuous state space is also replaced with a finite state space. This method is used in Miranda and Fackler (2002) to solve a variety of dynamic programming problems in economics. Applying this method improves the elapsed time to derive the equilibrium in the cases investigated by Salo and Tahvonen

(2001). In the case of iso-elastic demand, however, the value function cannot be obtained properly with small errors by the collocation method due to a problem related to function approximation with higher degree polynomials. So, one needs to use the first method to find the equilibrium in such a case where the collocation method cannot be applied. The approach to find the open-loop equilibrium is based on discretizing time and the iterations of extraction paths for all producers.

In reality, resource producers might differ in the costs of extraction because of dissimilar reserve types or utilized technology. Cost asymmetry among producers affects the supply of the firms in the market compared to asymmetric cost cases. Using the algorithm based on policy iteration and value function interpolation, the feedback equilibrium is computed assuming asymmetric costs as well as different initial reserve levels for the firms. We specifically examine the implications of cost asymmetry for the pattern of resource extraction by the firms.

Next, we investigate the effect of increasing the producers' resource stock on their profit. With zero production costs, Benchekroun and Van Long (2006) derive the conditions under which an increase in the reserve level will have a negative impact on a firm's profit. Using the method of policy iteration and value function interpolation to compute the feedback equilibrium, we extend the analysis of the effect of resource increase in the presence of extraction costs. We show that, similar to Benchekroun and Van Long (2006), it is possible that the profits of some firms reduce as a result of an increase in initial reserve. The reduction in profit depends on the relative initial stock of the firms in Benchekroun and Van Long (2006). We show that with a bounded iso-elastic demand and production costs, the reduction in profit depends on the relative cost of production by different firms.

3.2 Model

Suppose there are N producers endowed with an initial stock of an exhaustible resource. Each firm extracts its own resource stock, but supplies on the same market as other producers. q_i is the rate of change in firm i's resource stock or the supply of firm i. On the demand side, the demand function is given by $p = p(q)$, where $q = (q_1, .., q_N)$ is the vector of extraction rate for all firms. On the supply side, $s = (s_1, ..., s_N)$ is the state variable or the available level of reserve for all firms. Each producer has the unit extraction costs of $C_i(s_i)$, which can be either a linear or a non-linear function of the available stock of the firm, s_i. The current period profit of firm i is $q_i(p(q) - C_i(s_i))$. Each producer maximizes the present value of the future profits and so solves the following optimization problem:

$$\begin{aligned} &\max_{q_i \geqslant 0} \int_0^\infty q_i(p(q) - C_i(s_i))e^{-rt}dt \\ &\dot{s_i} = -q_i \\ &s_i(0) = s_{i0} \end{aligned} \tag{3.1}$$

$\dot{s_i}$ shows the rate of change in the resource by time. An open-loop strategy of a firm is a time path of extraction by that firm (Dockner, 2000; Haurie et al., 2012). In the open-loop equilibrium, each player's strategy maximizes the sum of its discounted profits given the optimal strategy of the other players. In such an equilibrium, the optimal strategy of firm i satisfies the optimality conditions of the Hamiltonian function:

$$H_i(x, q, t) = q_i(p(q) - C_i(s_i)) + \lambda_i(\dot{s_i} + q_i) \tag{3.2}$$

In the open-loop equilibrium, the strategy of firm i, q_i, depends only on time.

Now, suppose that at any moment each producer observes the available resource of all producers and condition its extraction on its own and the other firms' level of reserve. In fact, each firm i takes the other firms' strategy as given and determines its own optimal strategy $q_i(s(t), t) = \varphi_\mathrm{i}(\mathrm{s(t)})$ that optimizes the maximization problem in 3.1. This type of strategy, which is a rule that conditions the decision at any date on the state variable level at that date, is Markov-perfect strategy.

The equilibrium strategy in this case consists of the best reply of a player given other players' optimal strategy. The Markov perfect or feedback equilibrium strategy of each player satisfies the set of all Hamilton-Jacobi-Bellman (HJB) equations, assuming that the equilibrium strategies are continuous. The Hamilton-Jacobi-Bellman equation (HJB) for each player i has the following form:

$$\begin{aligned} & rV_i(s_1,...,s_N) = \max_{q_i \geq 0} \left\{ q_i(p(q) - C_i(s_i)) + V_i'(s_1,...,s_N) g_i(s_1,...,s_N,q_i) \right\} \\ & g_i(s_1,...,s_N,q_i) = -\dot{q}_i \end{aligned} \tag{3.3}$$

$V_i(s_1,...,s_N)$ shows the value of firm i at the current level of reserve. g_i is the transition function and shows the variation of reserve level with time. In order to find the path of optimal strategy, first the above functional equation should be considered for each firm. Solving N equations simultaneously gives the value function and the equilibrium strategy of each firm. The resulted extraction rates for all the firms represent the realization of the Nash feedback equilibrium which is subgame perfect.

In the simple case of $C_i(s_i) = 0$ and iso-elastic demand function, it can be shown analytically that there exists a feedback Nash equilibrium. In this case, the extraction rate of firm i on equilibrium depends only on its own level of reserve. There is also an analytical solution offered by Salo and Tahvonen (2001) under economic depletion with linear demand and a unit cost function which linearly depends on the reserve.

3.3 Resource extraction under economic depletion

The studies that model the oligopolistic competition in exhaustible resources mostly assume physical depletion of resources. These models neglect the fact that reserves are heterogeneous and that their complete physical depletion may not be possible. In this paper, we focus on economic depletion to give a more valid description of the reality of resource markets. The assumption of economic depletion of resources implies that the extraction cost will be more than the market price after the reserve reaches a certain level. In terms of conditions on the demand and cost functions in the model explained in the previous part, economic depletion implies that the production cost of the last unit of the resource is more than choke price: $C_i(0) > P(0)$.

3.3.1 Feedback equilibrium under economic depletion

In the dynamic game of exhaustible resources, the analytical solution to find the feedback equilibrium only exists for a few special cases such as iso-elastic demand combined with zero costs (Benchekroun and Van Long, 2006) and linear demand and linear unit costs under economic depletion (Salo and Tahvonen, 2001). Thus, to find the equilibrium, one should rely on numerical solutions. The numerical solution to find the feedback equilibrium in exhaustible resource oligopoly is only investigated, to the best of my knowledge, by (Salo and Tahvonen, 2001). Within the same framework of economic depletion, we extend the numerical analysis in (Salo and Tahvonen, 2001) to the cases with iso-elastic demand function. This functional form of demand is later used in the paper to see the effect of resource increase on producers' profit.

The numerical approach followed by (Salo and Tahvonen, 2001) is based on a Markov chain approximation of the HJB equation and iterating the policy function introduced by Dupuis and Kushner (1992). In this part, first the algorithm to find the feedback equilibrium in (Salo and Tahvonen, 2001), which is not shown in detail in their paper, is explained. Although this method uses a rather simple algorithm to find the equilibrium, it requires a large amount of computation time especially when the number of grid nodes of state space is large. An alternative solution in such cases might be to use the collocation method. This method, which will be explained in detail, is based on replacing the infinite-dimensional functional equation with a finite-dimensional root-finding problem. The computation time required in both methods is compared for a number of our simulations at the end of this part.

3.3.1.1 A method based on policy iteration and value function interpolation

Salo and Tahvonen (2001) extend the Markov chain approximation method introduced by Dupuis and Kushner (1992) for solving optimal control problems in the case of dynamic games. In this method the continuous time problem is transformed to a discrete time, discrete space problem. This could be done by discretizing the original Bellman equation and interpreting the results as a Markov chain. The optimal policy and the value function of all players could be reached by iterations in the policy function space. Similar to the study of Salo and Tahvonen (2001), the algorithm used in our paper to compute feedback equilibrium strategies is based on policy iteration in a discrete time discrete space framework. However, we use a more simple method to obtain the value function at different reserve levels.

Assume for simplicity that the grid points have a similar distance in all dimensions. Let h be the distance between the grid nodes, and Δt the step to discretize the time. The discrete time approximation of the Bellman equation will be:

$$\tilde{V}_i(s^l) = \underset{q_i \in q_i(S)}{max} \left\{ f_i(s^l, q_i, q_{-i})\Delta t + \beta^{\Delta t}\tilde{V}_i(g_i(s^l, q_i, q_{-i,}, \Delta t)) \right\} \tag{3.4}$$

According to Dupuis and Kushner (1992), it can be shown that, given the strategy of other players $q_{-i}(s)$, as $\Delta t \to 0$, the solution $\tilde{V}_i$ converges to the value function V_i of producer i. The following steps show the algorithm to find the feedback equilibrium:

1. Form an n-node discrete state space with nodes $s^l = (s^l_1, s^l_2, ..., s^l_N) \in S, l = 1, ..., n.$

2. Guess an initial value function and a policy for each player at all the grid nodes:$V_i(s^l) = V_i^0$, $q_i(s^l) = q_i^0$, $l = 1, ..., n$, $i = 1, ..., N$

3. For each player i:

   (a) Holding q_{-i} constant, find the policy vector q_i' that maximizes the right-hand side of the discrete Bellman equation.

   (b) Update the policy by $q_i' \to q_i$ and the value function by replacing the policy in the above expression.

   (c) If the change in the value function from the previous iteration is less than a determined tolerance, stop; otherwise return to step 3 for the same player.

4. If the change in the policy is less than a determined tolerance for all players, stop; otherwise return to step 3 for the other player.

To maximize the right-hand side of equation 3.4, we need to obtain the value of $\tilde{V}_i(g_i(s^l, q_i, q_{-i,}, \Delta t))$. In fact, this is the value function at the obtained state variable after the policy is implemented. Using the Markov chain approximation, Salo and Tahvonen (2001) obtain the value function in the new state by a proper weighing (interpreted as probabilities) of the value function in adjacent grid nodes. A more straight forward way is to obtain the value function at each level of state variable by the linear interpolation of value function at the grid nodes surrounding the new state variable.

For the simulations in this paper, the transition function g_i has the simple form of $g_i(s^l, q_i, q_{-i,}) = s_i^l - q_i \Delta t$ in discrete time. In a two players game, let the state which is reached from the grid node (s_1, s_2) in time step of Δt be $(s_1^{'}, s_2^{'}) = (s_1 - q_1 \Delta t, s_2 - q_2 \Delta t,)$. The amount of value function at $(s_1^{'}, s_2^{'})$ is the linear interpolation or the convex combination of the value function at four corner points shown in Figure 3.1 assuming that the grid nodes are equally distanced by a constant h. Compared to the collocation method, while the computation time is generally greater in this method, it has the advantage of simplicity in terms of programming.

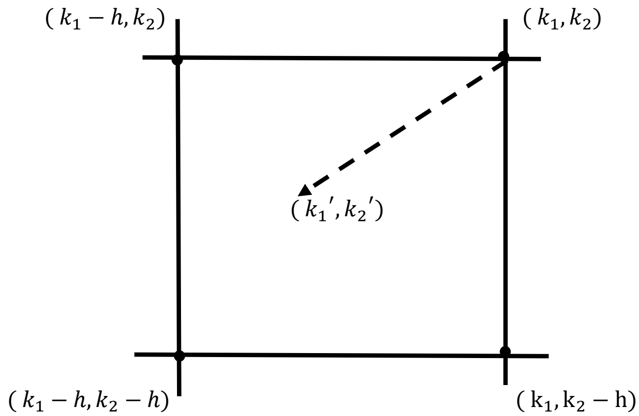

Figure 3.1: Transition from the initial state (s_1, s_2) to the state $(s_1^{'}, s_2^{'})$

3.3.1.2 Collocation method

The collocation method replaces an infinite-dimensional functional equation with a finite-dimensional root-finding problem (Miranda and Fackler, 2002). In essence, this method approximates the value function by linear combinations of polynomial basis functions with unknown coefficients. The unknown coefficients are then obtained by satisfying the value function at some specific state nodes.

For more than one player or the case of dynamic game, this numerical method should be applied to solve the system of Bellman equations simultaneously. This approach combines the methods of finding equilibrium in static games with those that are used to solve the Bellman equation for a single agent. Before moving to explain this method for dynamic game problems, it is worthwhile to briefly explain it in the static game of m players. Assume a static m-players game in which each player chooses its own action q_i from a set of possible actions. Each player i has a reward of $f_i(s, q_i, q_{-i})$ that depends on both actions of player i and the rest of the players,

$-i$. A vector of actions $q^* = (q_i^*, q_{-i}^*)$ is a Nash equilibrium if it satisfies $\underset{q_i}{max}\, f_i(s, q_i, q_{-i}^*)$ for every player.

To find q^* the following algorithm can be efficiently used:

1. Guess an initial value for q^*.
2. Update q^*: for each player i, take q_{-i}^* as given and find the optimal q_i^* by solving the maximization problem of player i.
3. Stop if the change in q^* from the previous iteration is smaller than the determined tolerance; otherwise return to step 2.

Subsequently, we consider the dynamic game of N players and explain the application of the collocation method in this case. At each period, each player observes the state variables as well as the decision of the other players. So, the reward of the player i, $f_i(s, q_i, q_{-i})$, is a function of all players' actions and the state variables. Each player looks for the optimal strategy q_i^* that maximizes the aggregate discounted rewards given the policies of the other players. In a discrete time framework, for each of N players there is a Bellmen equation as follows:

$$V_i(s) = \underset{q_i \in q_i(S)}{max} \left\{ f_i\{(s, q_i, q_{-i}^*(s)) + \beta V_i(g(s, q_i, q_{-i})), \quad s \in S \right\} \tag{3.5}$$

To find the value function and the policy of each player, the collocation method can be applied in the above functional equation. In this method, the value function of each player at n points in the state space, known as collocation nodes $s^l = (s_1^l, s_2^l, ..., s_N^l) \in S$, is approximated by a linear combination of some functions known as basis function.

$$V_i(s^l) \approx \sum_{j=1}^{n} c_{ij} \phi_j(s^l),\ l = 1, ..., n \tag{3.6}$$

For each player i, this value function should satisfy the Bellman equation at the collocation nodes. So we are looking for vector $c_i = (c_{i1}, ..., c_{in})'$ that satisfies the following approximation of the Bellman equation for player i.

$$\sum_{j=1}^{n} c_{ij}\phi_j(s^l) = \max_{q_i \in q_i(S)} \left\{ f_i(s^l, q_i, q_{-i}^l) + \beta \sum_{j=1}^{n} c_{ij}\phi_j(g(s^l, q_i, q_{-i}^l)) \right\}, \; l = 1, \ldots, n \tag{3.7}$$

q_{-i}^l are the optimal actions of the other players at state s^l. In essence, the collocation strategy allows us to replace the Bellman equation with Nn equations in Nn unknowns. The following steps briefly explain the algorithm which is used to derive the value function and policy function of all players:

1. Choose the degree of approximation n, a set of basis functions ϕ_j , and a set of collocation nodes s^l. Guess an initial value for the coefficient vectors c_i and action vectors q_i for every player i.

2. For each player i, determine the vector q_i that solves the above maximization problem, given the coefficient vectors and action of the other players.

3. If q_i' is the maximizing action vector in the previous step, update q_i by replacing it with q_i'.

4. Now use any iterative update rule such as $\Phi^{-1} v_i(c_i, q_{-i}) \to c_i$ to update the vector c_i.

5. Stop if the change in the coefficients value is less than a pre-determined tolerance, otherwise go to step 2.

In step 4, it is also possible to use the Newton method for iterating c_i. If the initial value is chosen properly, this method converges faster than function iteration. In this approach, choosing the type of basis function and the number of collocation nodes is an important issue. In general, a greater number of collocation nodes leads to a more accurate solution, and a greater computation time at the same time. Chebychev polynomial basis functions used jointly with Chebychev collocation nodes is a proper choice if the solution of the functional equation is sufficiently smooth (Miranda and Fackler, 2002).

One drawback of the collocation method is that, with large number of grid nodes and higher degree of Chebychev polynomial basis functions, the error terms in the approximation of value function might be large. This problem, known as Runge's phenomenon, happens when approximating particular functions by a polynomial of higher degree (Suli and Mayers, 2003). In our simulations with iso-elastic demand, for example, the value function cannot be properly approximated if the number of grid nodes is large. For such a demand function, it is not possible to apply the collocation method in high resolution of the state space. Thus, we need to apply the first method explained in the paper to properly find the equilibrium. The CompEcon toolbox, which accompanies Miranda and Fackler (2002), provides a useful set of MATLAB functions that could be used to simulate dynamic programming problems by the collocation method. A number of functions that are practical to create basis functions and collocation nodes as well as more complicated functions for dynamic game simulation are available in this toolbox.

For the feedback equilibrium simulation, both methods explained in the previous sections are used. For applying either method, first of all the discrete form of the Bellman equation 3.5 should be considered. In this equation the reward function is replaced by $f_i(s_i, q_i, q_{-i}) = q_i(p(q_i, q_{-i}) - C_i(s_i))$ for the purpose of our simulation. The transition function that gives the value of the state next period is $g(s_i, q_i, q_{-i}) = s_i - q_i$ in the deterministic case. The demand functions considered for the simulation are: linear demand: $p(q_1, q_2) = a - q_1 - q_2$, $a > 0$, exponential demand: $p(q_1, q_2) = a\, exp(-q_1 - q_2)$, $a > 0$, and iso-elastic demand: $p(q_1, q_2) = b(a + q_1 + q_2)^{-\alpha}$, $a > 0$, $b > 0$. The cost function can be constant or increasing with state either in linear $C(s_i) = c - ds_i$ or in exponential $C(s_i) = c\, exp(-s_i) + d$ form. The simulation parameters for each case are indicated along with the figures in all parts.

The chosen grid and basis functions are Chebychev collocation nodes with ($n_1 = n_2 = 20$) or a 400 nodes grid and Chebychev polynomial basis functions. The nodes for the first method are chosen linearly with the same number of 400.

Figures 3.2-a to 3.2-f give examples of the equilibrium policy or the equilibrium extraction rate. For the functions in Figures 3.2-a to 3.2-d, we obtain similar results to those in Salo and Tahvonen (2001) by using the collocation method. In general, with any form of the demand and the cost function, the extraction rate of each player increases in its own stock and decreases in the rival's stock. Figure 3.2-a approximates the analytical solution in the case of linear demand and linear unit costs. Although the equilibrium extraction rate seems linear in the different regions, it is nonlinear considering the whole state space.

In the linear unit cost case (Figures 3.2-a, 3.2-c, 3.2-e), there are some values of the resource stock in which one of the producers does not extract. This happens for the producer with a relatively lower level of the stock. With the non-linear costs, the strategy has a clearly non-linear form for all the demand functions. There are some resource levels with zero production of one player which are negligible when compared to the linear unit cost cases.

Figure 3.3 shows the phase diagram for the reserve state space in the feedback equilibrium. The phase diagram of resource use in the case of iso-elastic demand (Figures 3.3-e to 3.3-f) has a similar pattern to the cases investigated by Salo and Tahvonen (2001). The slope of the each path is equal to the ratio of the extraction rate, q_2/q_1. So, a higher slope shows a bigger market share for player 2. A producer with higher resource always has a greater share of the market. As can clearly be seen in the figure, close to origin the equilibrium must converge to a turnpike trajectory with equal market share for both firms. This happens when there is cost symmetry, which is the case in our examples. Comparing the left-hand-side figures with those on the right-hand side reveals that with the same cost function, the different functional form of the demand does not affect the general pattern of relative extraction.

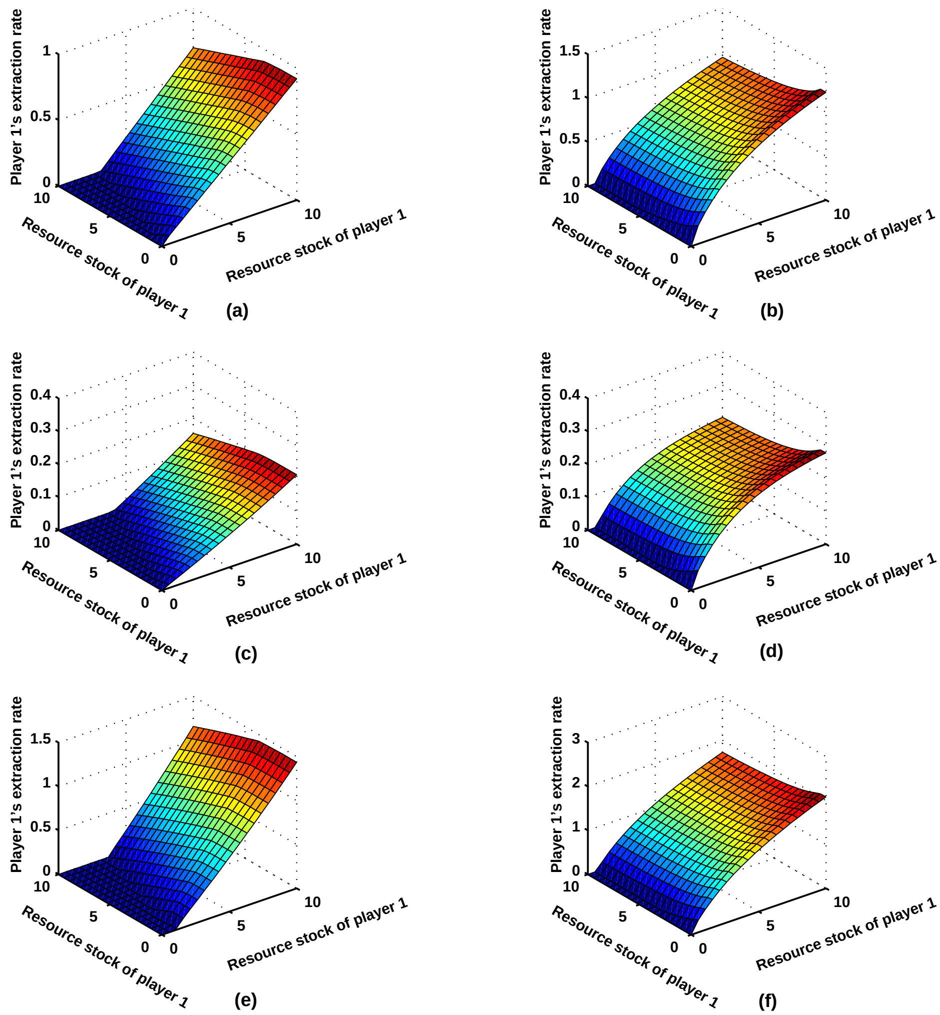

Figure 3.2: Feedback equilibrium extraction rate for different functional forms: (2-a) Linear demand, linear costs,$a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. (2-b) Linear demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$, $p(q) = a - q_1 - q_2$, $C(s_i) = c\,exp(-s_i) + d$. (2-c) Exponential demand, linear costs, $a = 10$, $c = 10$, $d = .5$ $p(q) = a\,exp(-q_1 - q_2)$, $C(s_i) = c - ds_i$. (2-d) Exponential demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$ $p(q) = a\,exp(-q_1 - q_2)$, $C(s_i) = c\,exp(-s_i) + d$. (2-e) Iso-elastic demand, linear costs, $a = 30$, $b = 10$, $c = 10$, $d = .5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C_i(s_i) = c - ds_i$. (2-f) Iso-elastic demand, non-linear costs, $a = 30$, $b = 10$, $c = 5$, $d = 5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C(s_i) = c\,exp(-s_i) + d$.

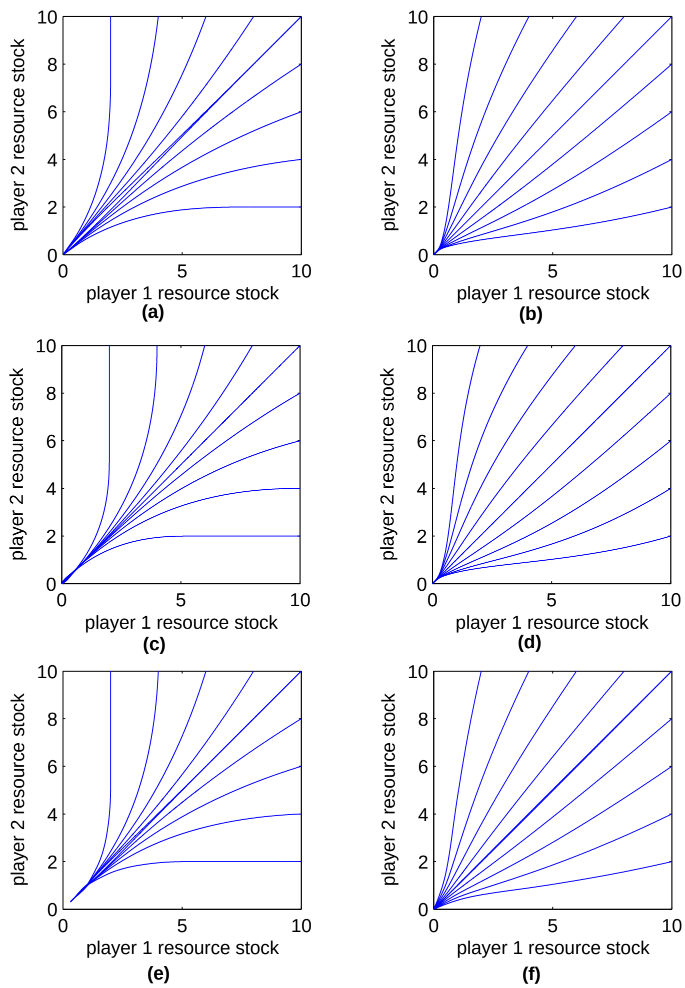

Figure 3.3: Phase diagrams for the state space in the feedback equilibrium: (3-a) Linear demand, linear costs, $a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. (3-b) Linear demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$, $p(q) = a - q_1 - q_2$, $C(s_i) = c\, exp(-s_i) + d$. (3-c) Exponential demand, linear costs, $a = 10$, $c = 10$, $d = .5$, $p(q) = a\, exp(-q_1 - q_2)$, $C(s_i) = c - ds_i$. (3-d) Exponential demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$ $p(q) = a\, exp(-q_1 - q_2)$, $C(s_i) = c\, exp(-s_i) + d$. (3-e) Iso-elastic demand, linear costs, $a = 30$, $b = 10$, $c = 10$, $d = .5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C_i(s_i) = c - ds_i$. (3-f) Iso-elastic demand, non-linear costs, $a = 30$, $b = 10$, $c = 5$, $d = 5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C(s_i) = c\, exp(-s_i) + d$.

Convergence to the turnpike of the equal share shows an increase in the share of the lower resource owner with time. The convergence can be seen with the linear cost function (Figures 3.3-a, 3.3-c, and 3.3-e). However, with a non-linear cost function (Figure 3.3-b, 3.3-d, and 3.3-f), the share of the high resource producer initially increases, leading to a temporary divergence of the path. This happens because the non-linear cost function is relatively constant and independent of the reserve level when the resource value is high. These results do not correspond to the earlier studies in which the share of the high resource producer increases with time. In the models such as "oil'igopoly" all the resource is exploited by a monopoly at the end. With a reserve-dependent cost function and economic depletion, the share of the producer with a lower reserve increases with time. In fact, with lower extraction and higher price, the higher-cost producers with essentially higher unit costs have incentives to enter the market.

As was mentioned earlier, using the method based on policy iteration and value function interpolation is a more straightforward approach to find the equilibrium with a relatively simpler algorithm to be coded. However, the computation time in this method might be considerable especially in the simulations with a larger number of grid nodes. The following table compares the elapsed time to find the feedback equilibrium in two of the simulations illustrated in figure 3.2 with a different number of grid nodes.[1]

Table A.1: Computation time for two alternative methods to find feedback equilibrium

	Number of grid nodes	Collocation	Policy iteration & value function interpolation
linear demand, linear cost	100	4 sec.	298 sec
linear demand, non-linear cost	400	4 sec	711 sec
non-linear demand, linear cost	100	7 sec	379 sec
non-linear demand, non-linear cost	400	33 sec	1535 sec

[1]The required time presented in this table were obtained on an Intel Core(TM) i3 3.30 GHz CPU system with 8GB RAM running Windows 7. The mentioned times are required to reach accuracy 10^{-3} for the largest change in value function and extraction rate in the method based on policy iteration and value function interpolation and for the largest change in the coefficients of basis functions in the collocation method.

3.3.2 Open-loop equilibrium under economic depletion

The majority of the studies that model dynamic game in the exhaustible resource market focus on the open-loop equilibrium. In general, it is easier to find the solution analytically in the open-loop compared to the feedback problems. The drawback of such equilibrium is that if one of the players deviates from the equilibrium extraction path, then it will no longer be optimal for the rest of the players to follow the equilibrium strategy. Thus, precommitment to the equilibrium path of production is essential for this type of game. In order to solve the problem, the maximum principle is applied to the Hamiltonian equation (2.2) of each player:

$$\begin{aligned}&\tfrac{\partial H_i}{\partial q_i} = 0\\&\lambda_i = r\lambda_i - \tfrac{\partial H_i}{\partial s_i}\end{aligned} \tag{3.8}$$

In the game of N players, the analytical approach involves solving a system of equations obtained by applying the maximum principle to the Hamiltonian equation of all the players along with the transversality conditions $\underset{t\to\infty}{lim}\ s_i\lambda_i = 0\, i = 1, ..., N$. Solving this system of equations is only possible assuming a number of simple forms of demand and cost functions. To solve the problem with a wide range of functional forms, we use a numerical approach.

The algorithm to find the open-loop equilibrium is based on considering the main maximization problem in the finite and discrete time. Referring to equation 3.1, the maximization problem of firm i has the form of:

$$\begin{aligned}&\underset{q_i\geqslant 0}{max} \int_0^\infty q_i(p(q) - C_i(s_i))e^{-rt}dt\\&\dot{s_i} = -q_i\\&s_i(0) = s_{i0}\end{aligned}$$

Let T be the finite time horizon and $\triangle\, t$ the time interval between discrete time points. These discrete times are shown by $\tilde{t} = \triangle\ t, 2\ \triangle\ t, ..., T$. Considering the problem in finite time is inevitable while one is trying a numerical approach. In practice, the horizon is extended so that the remaining resource reaches a predetermined level. The optimization problem in discrete and finite time horizon will have the following form:

$$\begin{aligned} &\max_{q_i \geq 0} \sum_{\tilde{t}=\triangle t}^{\tilde{t}=T} (q_i(\tilde{t})(p(q(\tilde{t})) - C_i(s_i(\tilde{t})))(\triangle\, t)\beta^{\tilde{t}} \\ &s.t. \quad s_i(\tilde{t} + \triangle\, t) = s_i(\tilde{t}) - q_i(\tilde{t}) \\ &s_i(0) = s_{i0} \end{aligned} \tag{3.9}$$

As $\triangle\, t \to 0$, the problem will be closer to the continuous time form. To further simplify the problem, we can merge the state variation equation with the objective problem. This can be done by replacing the state variable $s_i(\tilde{t})$ using the state variation equation. As a result, the maximization problem will have the following form:

$$\max_{q_i(\tilde{t}) \geq 0} \sum_{\tilde{t}=\triangle t}^{\tilde{t}=T} q_i(\tilde{t})(p(q(\tilde{t})) - C_i(s_i(0), q_i(\triangle\, t), q_i(2 \triangle\, t), ..., q_i(\tilde{t}))(\triangle\, t)\beta^{\tilde{t}} \tag{3.10}$$

A number of iterations on the strategies of all players will then lead to finding the equilibrium strategy. This algorithm could be used where it is possible to replace the state variation equation in the objective function. By doing so, the state variation equation is implicitly considered in the objective function. The maximization problem will then be the same as maximizing a sum of discounted profit without any constraint.

In essence, the numerical algorithm to find the open-loop equilibrium strategy for each player is as follows:

1. Consider the discrete form of the objective function and the state transition equation (3.9).
2. Consider a time horizon T and discretize it to small increment $\triangle t$.
3. Assume an initial extraction path for each player: $q_i(\tilde{t}) = q_i^0(\tilde{t})$
4. For each player $i = 1, ..., N$

(a) Holding $q_{-i}(\tilde{t})$ constant, find the extraction path of player i, $q_i'(\tilde{t})$, that maximizes the objective function in 3.10.

(b) Update $q_i(\tilde{t})$ by $q_i'(\tilde{t}) \to q_i(\tilde{t})$

(c) If difference in the policy $q_i(\tilde{t})$ from previous step is less than a determined tolerance for all players, stop; otherwise go to step 4 for the other player.

5. If $s_i(T)$ is less than a predetermined level of reserve[2] for all players stop; otherwise $T + 10 \to T$ and go to step 1.

Only a few studies compare the open-loop and feedback equilibrium in an exhaustible resource oligopoly. Polasky (1990) shows that, in a discrete time model with a finite number of producers, open-loop and feedback equilibriums differ. Using a cartel-fringe framework with linear demand and constant marginal extraction costs, Benchekroun and Withagen (2008) show that feedback and open-loop equilibriums coincide in the limit with an infinite number of fringe firms if fringe members are price takers. By using the suggested numerical method, it is possible to obtain the open-loop equilibrium for the same demand and cost functions for which the feedback equilibrium has been derived. Figure 3.4 is associated with the resulted phase diagrams of resource use with the open-loop strategies. There is no clear difference in the phase diagrams between the open-loop and the feedback cases. It is then interesting to see the implications of both types of equilibrium for the path of extraction.

For the open-loop equilibrium, the path of extraction is the direct result of solving the optimization problem. In the feedback case, after obtaining the equilibrium strategy, one can get the path of extraction by simulating a game between the two players who have the obtained equilibrium strategies. Figure 3.5 displays the extraction rate in the initial 50 years with feedback strategies where the demand and the unit costs are both linear.

[2]This predetermined level of reserve is greater than the lowest attainable reserve by a small tolerance. The lowest attainable reserve can be obtained from equalizing the unit cost function to choke price.

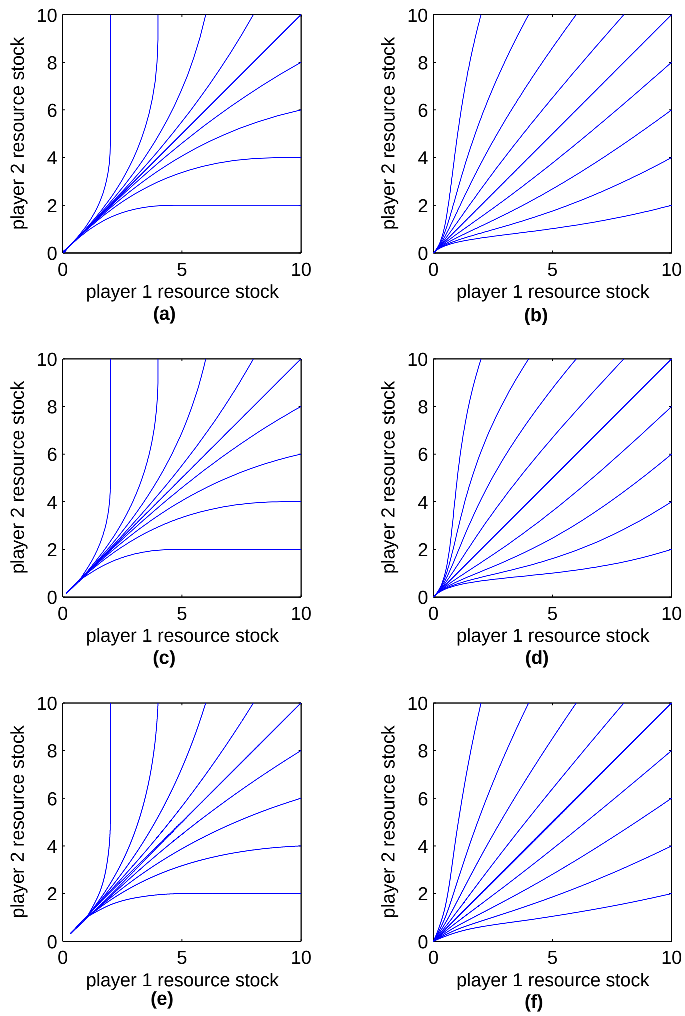

Figure 3.4: Phase diagrams for the state space in the open-loop equilibrium: (4-a) Linear demand, linear Costs, $a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. (4-b) Linear demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$, $p(q) = a - q_1 - q_2$, $C(s_i) = c\,exp(-s_i) + d$. (4-c) Exponential demand, linear costs, $a = 10$, $c = 10$, $d = .5$, $p(q) = a\,exp(-q_1 - q_2)$, $C(s_i) = c - ds_i$. (4-d) Exponential demand, non-linear costs, $a = 10$, $c = 5$, $d = 5$ $p(q) = a\,exp(-q_1 - q_2)$, $C(s_i) = c\,exp(-s_i) + d$. (4-e) Iso-elastic demand, linear costs, $a = 30$, $b = 10$, $c = 10$, $d = .5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C_i(s_i) = c - ds_i$. (4-f) Iso-elastic demand, non-linear costs, $a = 30$, $b = 10$, $c = 5$, $d = 5$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C(s_i) = c\,exp(-s_i) + d$.

Figures 3.6 and 3.7 display the extraction paths in both feedback and open-loop equilibriums separately for each player. While the extraction rate of the producer with higher resource decreases with time, the other producer might initially have an increasing rate of extraction. This pattern is similar in both feedback and open-loop equilibriums; however, the paths of extraction in the two types of equilibrium do not coincide. The non equivalence of open-loop and feedback extraction paths in our study confirms the earlier findings by Benchekroun and Withagen (2008) in a cartel-fringe framework with linear demand and constant marginal costs. Benchekroun and Withagen (2008) show that, with a finite fringe number, there exists no feedback equilibrium that replicates the open-loop extraction path.

3.3.3 Feedback equilibrium with cost asymmetry among producers

Up to now, it has been assumed that the cost function is similar for the different producers. In reality, there is heterogeneity among the producers in terms of cost function. In the case of oil or natural gas production, there is a number of large-scale companies as well as a range of smaller producers. Larger-scale companies might take advantage of more advanced technologies and have lower marginal costs compared to smaller producers. On the other hand, the costs of extraction depend, to a great extent, on the type and accessibility of the oil field. According to IEA (2009), the costs of piping a barrel of oil out of the ground range from 17$ to 52$.

In this part, this heterogeneity is taken into account in the simulations in order to characterize the feedback equilibrium more precisely. In the simulation, the cost function of the first firm is the same as before, but the costs of the second firm are 20% higher at any reserve level in all cases. Increasing the costs of the second player changes the phase diagram of resource extraction, as can be seen in Figure 3.8. In the cases with linear unit costs (3.8-a, 3.8-c, and 3.8-e), the paths of the resource change converge to a turnpike with a greater share for the first player. This is in contrast with the asymmetric cots case investigated in the previous

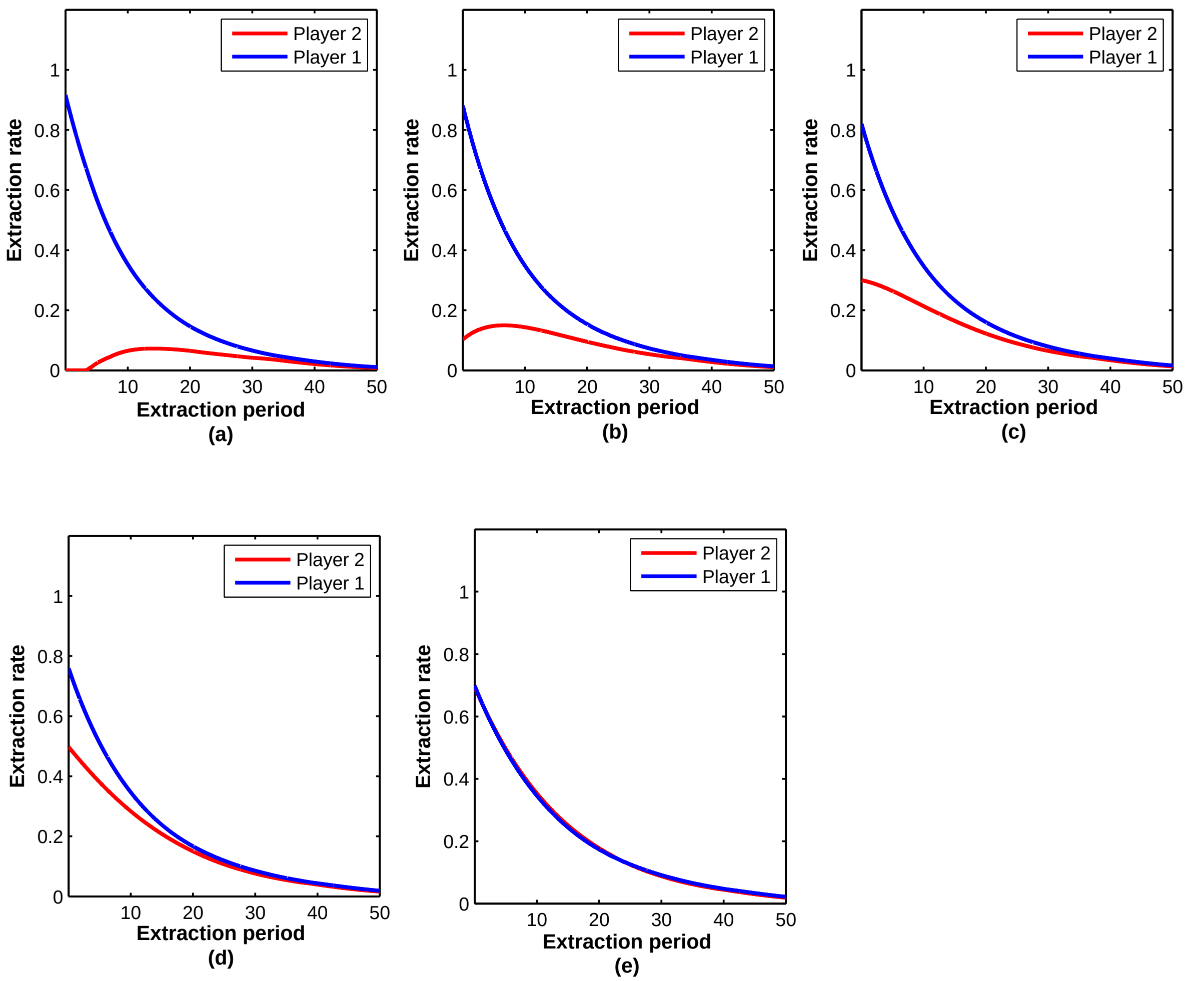

Figure 3.5: Path of extraction rate in feedback equilibrium for Linear demand, linear Cost: $a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. Initial reserves: (5-a) $s_{10} = 10$, $s_{20} = 2$, (5-b) $s_{10} = 10$, $s_{20} = 4$, (5-c) $s_{10} = 10$, $s_{20} = 6$, (5-d) $s_{10} = 10$, $s_{20} = 8$, (5-e) $s_{10} = 10$, $s_{20} = 10$.

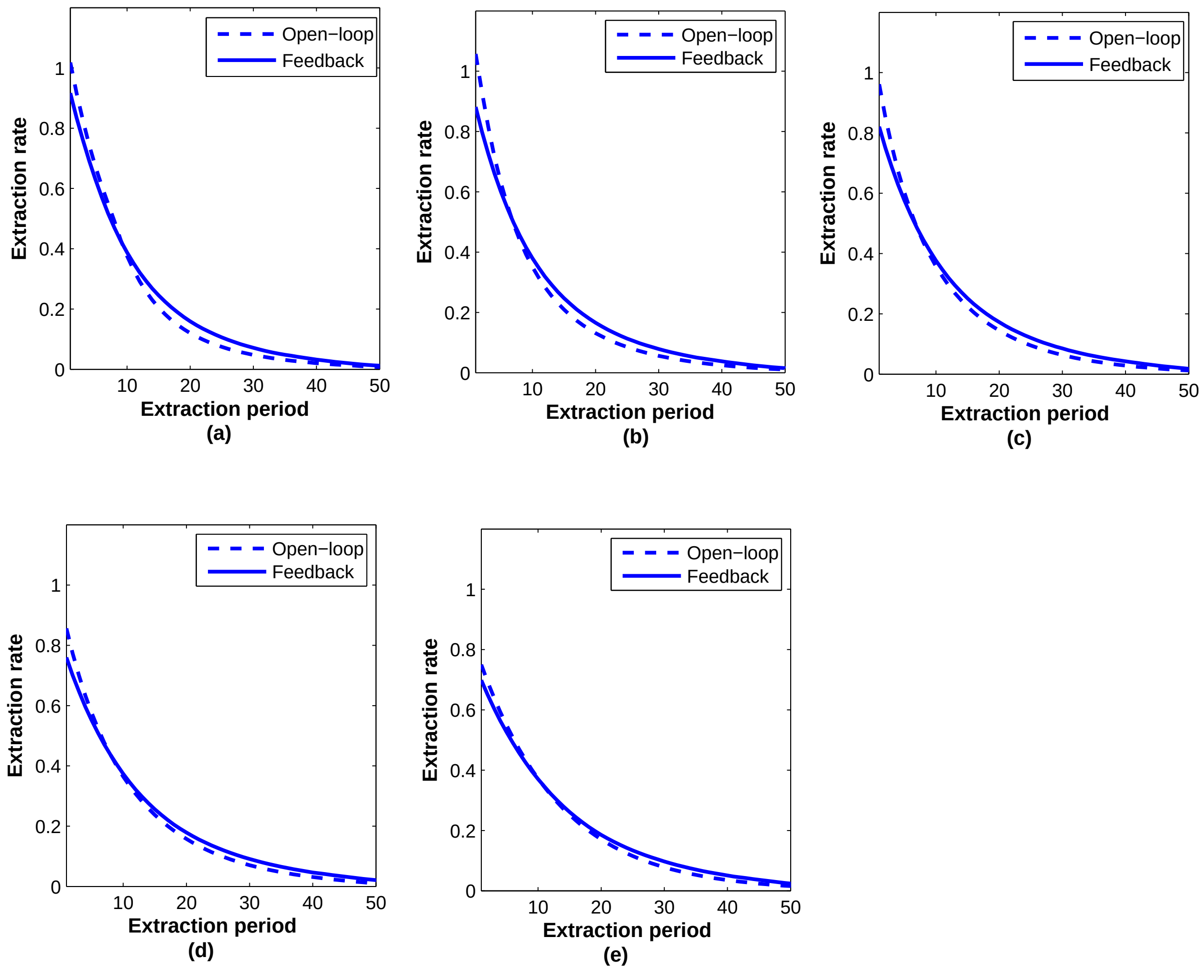

Figure 3.6: Path of extraction rate in feedback and open-loop equilibrium for the first player for Linear demand, linear Cost: $a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. Initial reserves: (5-a) $s_{10} = 10$, $s_{20} = 2$, (5-b) $s_{10} = 10$, $s_{20} = 4$, (5-c) $s_{10} = 10$, $s_{20} = 6$, (5-d) $s_{10} = 10$, $s_{20} = 8$, (5-e) $s_{10} = 10$, $s_{20} = 10$.

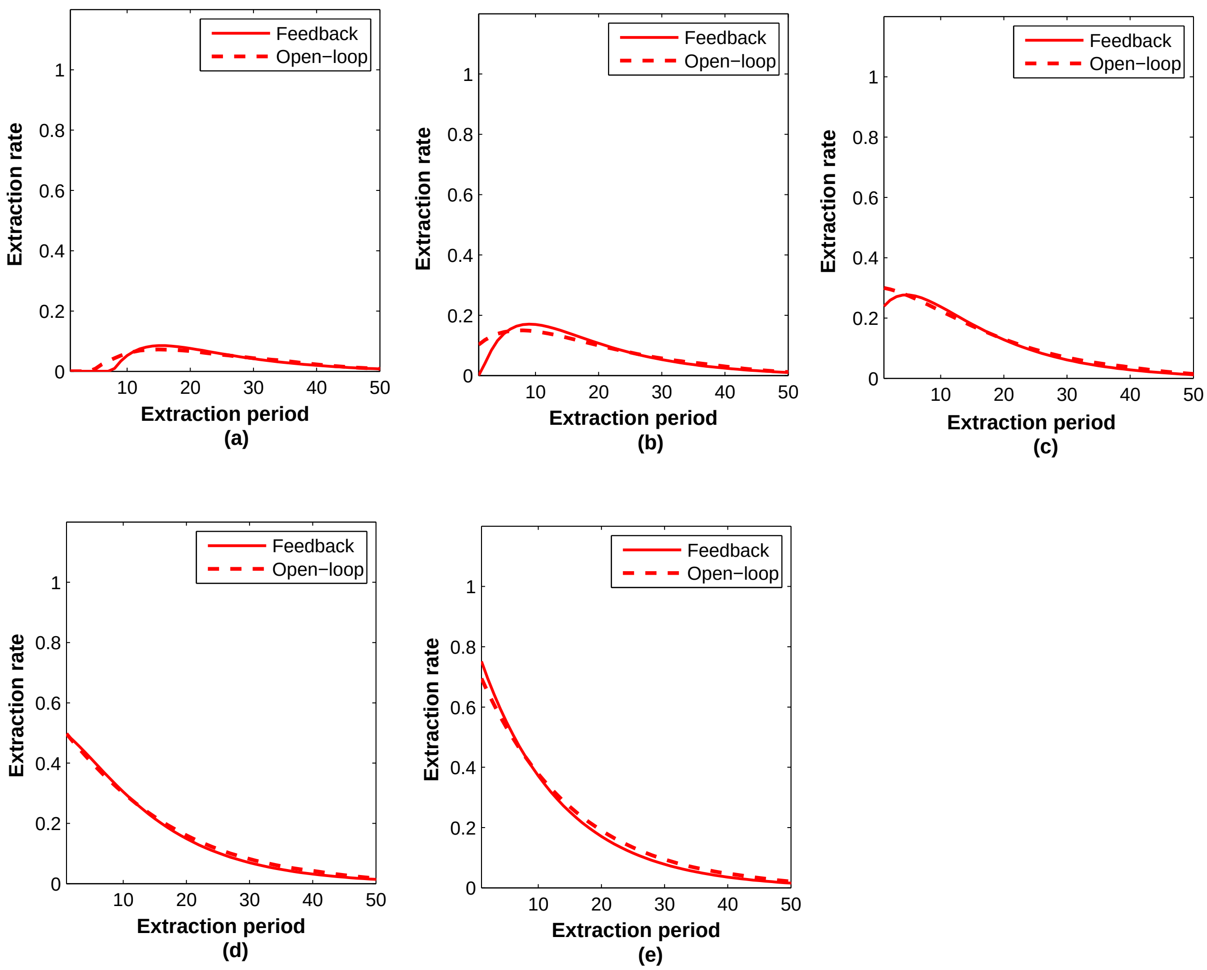

Figure 3.7: Path of extraction rate in feedback and open-loop equilibrium for the second player for Linear demand, linear Cost: $a = 10$, $c = 10$, $d = .5$, $p(q) = a - q_1 - q_2$, $C_i(s_i) = c - ds_i$. Initial reserves: (5-a) $s_{10} = 10$, $s_{20} = 2$, (5-b) $s_{10} = 10$, $s_{20} = 4$, (5-c) $s_{10} = 10$, $s_{20} = 6$, (5-d) $s_{10} = 10$, $s_{20} = 8$, (5-e) $s_{10} = 10$, $s_{20} = 10$.

section with an eventually equal share of the players. Additionally, in low levels of initial resource there is no extraction by the second player since price will be less than unit costs for all resource levels.

Figures 3.8-b, 3.8-d, and 3.8-e are related to non-linear costs cases. In the non-linear costs cases of Figure 3.8, the slope of any trajectory is lower almost all along the path compared to similar trajectory in Figure 3.3 (the case of symmetric costs). This can be clearly seen by comparing the trajectories starting with a lower initial resource of the second player. The convex trajectories of Figure 3.3 are replaced by concave paths in Figure 3.8, showing an increase in the share of the first player. So, increasing the costs of the second player will decrease the share of this player compared to the symmetric case. Salo and Tahvonen (2001) indicate that a model with economic depletion will lead to a decrease in market concentration over time. So, the producers that only differ in initial resource level will eventually have the equal extraction rates in the market. However, the analysis in this part shows this result will not hold when costs differ among producers. Non-renewable resource producers will not eventually have equal market share if, in addition to the initial reserve, costs also differ among producers.

3.4 The effect of resource stock change on producers' profit

Benchekroun and Van Long (2006) look at the effect of resource discovery on the profit of non-identical resource producers. With an unbounded iso-elastic demand and zero costs, the optimal strategy can be obtained analytically. Benchekroun and Van Long (2006) show that in this case an increase in the resource of the firms might decrease the profit of some firms. For example, a uniform absolute increase of resource for all firms will reduce a firm's profit if $\frac{s_i}{(\sum_{k=1}^{N} s_k)} > \frac{1}{\alpha N}$, where s_i is the initial resource level of firm i, N is the number of firms and α is the demand elasticity. This condition implies that an increase in the stock of the firms with

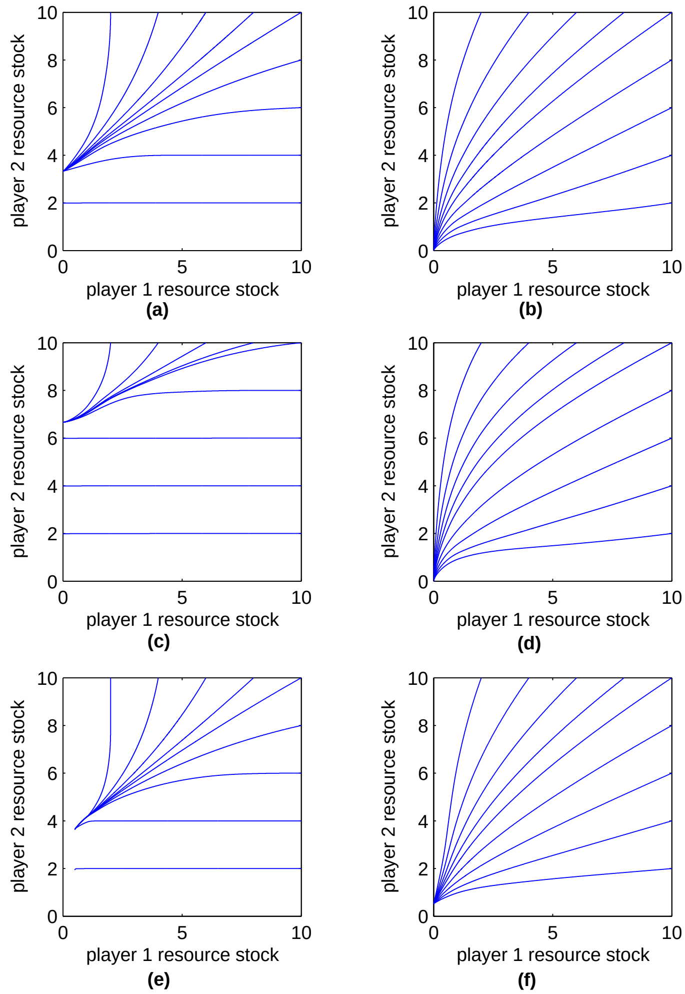

Figure 3.8: Phase diagrams for the state space with asymmetric costs: (8-a) Linear demand, linear costs,$a = 10$, $c_1 = 10$, $c_2 = 12$, $d_1 = 0.5$, $d_2 = 0.6$, $p(q) = a - q_1 - q_2$, $C_1(s_1) = c_1 - d_1 s_1, C_2(s_2) = c_2 - d_2 s_2$. (8-b) Linear demand, non-linear costs, $a = 10$, $c_1 = 5$, $c_2 = 6$, $d_1 = 5\, d_2 = 6$, $p(q) = a - q_1 - q_2$, $C_1(s_1) = c_1\, exp(-s_1) + d_1$, $C_2(s_2) = c_2\, exp(-s_2) + d_2$. (8-c) Exponential demand, linear costs, $a = 10$, $c_1 = 10$, $c_2 = 12$, $d_1 = 0.5$, $d_2 = 0.6$ $p(q) = a\, exp(-q_1 - q_2)$, $C_1(s_1) = c_1 - d_1 s_1, C_2(s_2) = c_2 - d_2 s_2$. (8-d) Exponential demand, non-linear costs, $a = 10$, $c_1 = 5$, $c_2 = 6$, $d_1 = 5\, d_2 = 6$ $p(q) = a\, exp(-q_1 - q_2)$, $C_1(s_1) = c_1\, exp(-s_1) + d_1$, $C_2(s_2) = c_2\, exp(-s_2) + d_2$. (8-e) Iso-elastic demand, linear costs, $a = 30$, $b = 10$, $c_1 = 10$, $c_2 = 12$, $d_1 = 0.5$, $d_2 = 0.6\, \alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$,$C_1(s_1) = c_1 - d_1 s_1$, $C_2(s_2) = c_2 - d_2 s_2$. (8-f) Iso-elastic demand, non-linear costs, $a = 30$, $b = 10$, $c_1 = 10$, $c_2 = 12$, $d_1 = 0.5$, $d_2 = 0.6\, \alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, $C_1(s_1) = c_1\, exp(-s_1) + d_1$, $C_2(s_2) = c_2\, exp(-s_2) + d_2$

larger stocks may have a negative effect on their profit.

In the presence of extraction costs it is no longer possible to obtain the analytical solution or derive an explicit relation such as the above condition. By using any of the numerical approaches to find the feedback equilibrium, it is possible to find the effect of resource increase on producers' profit. Similar to Benchekroun and Van Long (2006), the additional resource is distributed uniformly to both producers competing in a market with iso-elastic demand. There is an asymmetry in terms of initial reserve among producers. Price should be bounded in order to avoid the boundary problems in the numerical solution. The profits at different initial stock levels are obtained for the iso-elastic demand with two elasticity of $\alpha = 0.5$ and $\alpha = 0.9$. We consider the cases with zero costs and identical unit costs as well as non-identical costs, with either the smaller producer or the larger one producing with lower costs.

The effect of a non-marginal change in resource endowment on producers' total profit is displayed in Figures 3.9 and 3.10. In general, with zero or equal extraction costs, the total profit of the smaller producer converges to that of the other one as more resource is added to the initial reserve. As is expected, profits are higher in the inelastic case (Figure 3.9). In this case, there is no drop in the total profit as more resource is distributed to the producers. However, with a more elastic demand, increasing the initial reserve might have a negative impact on total profit. As can be seen in Figures 3.10-c and 3.10-d, the decrease in total profit occurs for the high cost producer.

By using the numerical approaches, the results of Benchekroun and Van Long (2006) are extended to the cases with production costs. In terms of the effect of elasticity, our results are similar to those of Benchekroun and Van Long (2006) with zero costs. In a market with a more elastic demand, it is more plausible that the profit of some firms reduces with an increase in initial resource stock. However, when production costs exist, the conditions under which a firm might face a reduction in production are different from what is obtained in their study. Assuming an unbounded iso-elastic demand and zero costs, Benchekroun and Van Long (2006)

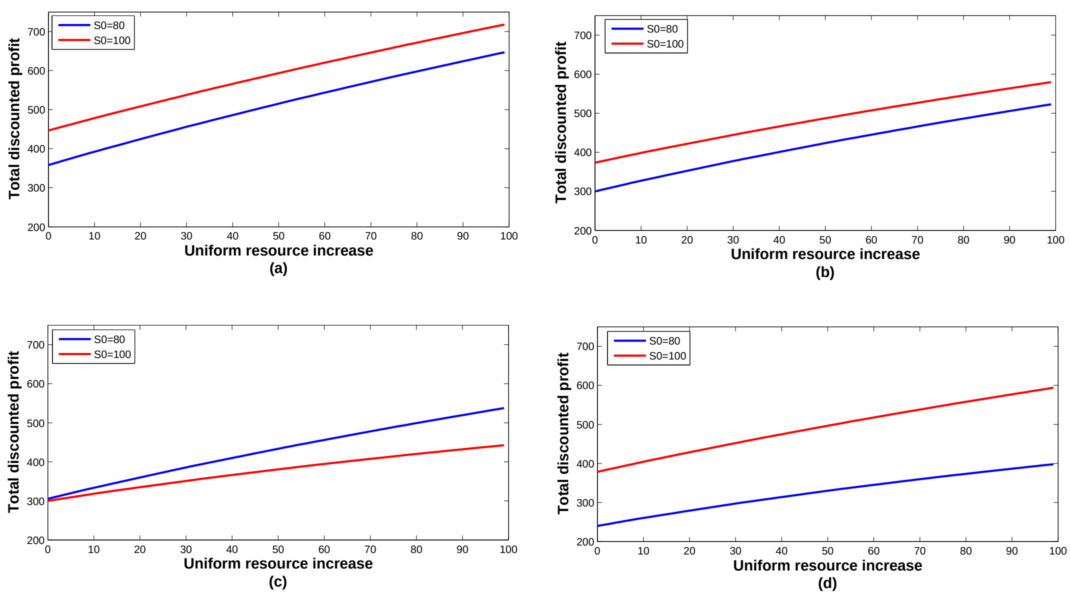

Figure 3.9: Total discounted profit as a function of uniform resource increase to the initial reserve: Demand function, $a = 30$, $b = 10$, $\alpha = 0.5$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, (9-a) Zero costs, $C_1 = 0$, $C_2 = 0$. (9-b) Equal costs, $C_1 = 1$, $C_2 = 1$. (9-c) Unequal costs, $C_1 = 1$, $C_2 = 2$. (9-d) Unequal costs, $C_1 = 2$, $C_2 = 1$.

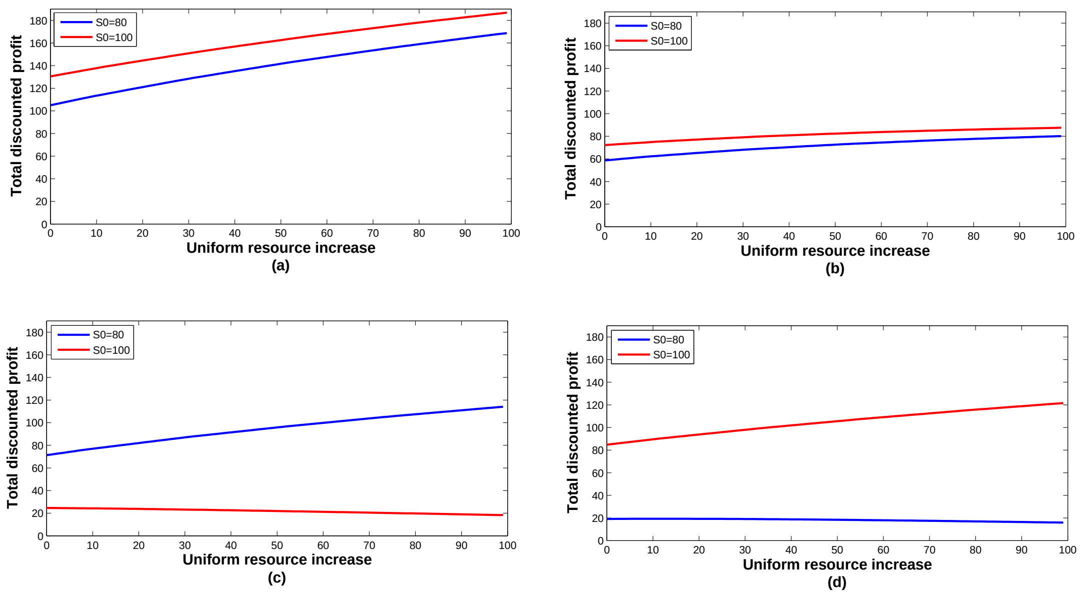

Figure 3.10: Total discounted profit as a function of uniform source increase to the initial reserve: Demand function $a = 30$, $b = 10$, $\alpha = 0.9$, $p(q) = b(a + q_1 + q_2)^{-\alpha}$, (10-a) Zero costs, $C_1 = 0$, $C_2 = 0$. (10-b) Equal costs, $C_1 = 1$, $C_2 = 1$. (10-c) Unequal costs, $C_1 = 1$, $C_2 = 2$. (10-d) Unequal costs, $C_1 = 2$, $C_2 = 1$.

show that larger firms might have a decrease in profit as resource increases uniformly for all firms. Our analysis shows that, with a bounded iso-elastic demand and non-zero costs, it is the high cost producer that might face a reduction in total profit. Thus, with non-zero costs, decrease in profit depends on the relative costs of production rather than the relative initial reserve.

3.5 Conclusion

Producers' competition in an exhaustible resource market can be modeled in a dynamic game framework. The previous studies mostly focus on the open-loop equilibrium of this game which assumes that each player can make a credible precommitment to follow the equilibrium strategies. Markov-perfect or feedback equilibrium, in which the action of players is conditioned to the observed state variable at any date, more corresponds to the reality of competition in resource markets. However, this type of equilibrium can be derived analytically only in a few special cases with specific cost and demand functions.

In this paper, we mainly focus on feedback equilibrium and economic instead of physical depletion of resources. First, we extend the analysis in Salo and Tahvonen (2001) by considering an iso-elastic demand. Confirming the results of Salo and Tahvonen (2001) on relative share of producers, with reserve-dependent costs and economic depletion, the share of the producer with a lower reserve increases with time, and so market concentration decreases. Deriving the feedback equilibrium with this type of demand is needed for further analysis of Benchekroun and Van Long (2006)'s study on the effect of resource increase on producers' profit. Using the numerical approach to derive the open-loop equilibrium, we derive the equilibrium strategies for all the functional forms in Salo and Tahvonen (2001) as well as the case of iso-elastic demand.

To find the feedback equilibrium, two different methods are applied in the simulations. The first algorithm is similar to the one used by Salo and Tahvonen (2001) and is based on the search of optimal strategy in a discrete state space and interpolation of value function. Another method with less computation time, specifically in higher resolution of discretizing the state space, is the collocation method. This method, which replaces the infinite-dimension HJB equation with a finite-dimension root-finding problem, is a fast and flexible method that can be used to find the feedback equilibrium in both deterministic and stochastic cases. The suggested algorithm to find the open-loop equilibrium is based on transforming the problem to a discrete and finite time problem and iteration of extraction paths.

Using the method based on policy iteration and value function interpolation, we extend the analysis in Benchekroun and Van Long (2006) that investigates the change in the profit of exhaustible resource producers caused by an increase in their stock. We consider the case with non-zero production costs and show that, in accordance with Benchekroun and Van Long (2006) in the zero-costs case, increasing the initial resource might have a negative impact on profit.

Appendix

The following MATLAB codes correspond to the algorithm to find the feedback equilibrium explained in 3.1.1.

```
clc
clear all
format long
nn=10;                 % #of grid nodes in each direction
tol=0.001;             % tolerance for value function
tol_q=0.001;           % tolerance for extraction rates
h=0.1;                 % time ahead

for fn=1:6             % function number from q_feedback

    j=10;
    x1_max=j;          % initial resource for player 1
    x2_max=j           % initial resource for player 2

    q1_0=zeros(nn,nn)+1;    % initial values for the extraction rates
    q2_0=zeros(nn,nn)+1;

    v_01=10*ones(nn,nn);    % initial values for value functions
    v_02=10*ones(nn,nn);

    dif_q1=1;dif_q2=1;      % initial values for differences

    i=1;                    % if i odd: player 1, if even: player 2


    %%%%%%%%% the game between 2 players

    %%%%%%%% Two main inputs of q_feedback are the value function of the same player and the
    %%%%%%%% extraction rates of the other player
    %%%%%%%% The main output are updated optimal extraction and value function of the same
    %%%%%%player

    while dif_q1>tol_q || dif_q2>tol_q    % until strategies dif. from previous iteration small

        if mod(i,2)==1                    % player 1


            [q1 v_01 v_02]=q_feedback(q2_0,x1_max,x2_max,nn,mod(i,2),fn,h,tol,v_01,v_02);
            dif_q1=max(max(abs(q1-q1_0))) % change from the previous strategy
            q1_0=q1;                      % updating player 1 strategy
        else                              % player 2

            [q2 v_01 v_02]=q_feedback(q1_0,x1_max,x2_max,nn,mod(i,2),fn,h,tol,v_01,v_02);
            dif_q2=max(max(abs(q2-q2_0))) % change from the previous strategy
            q2_0=q2;                      % updating player 1 strategy
        end

        i=i+1;                            % changing the player
    end



    q11=q1;            % equilibrium strategy of player 1
    q22=q2;            % equilibrium strategy of player 2

end
```

```
% for player 1: q_feedback takes the value function of player 1 and the extraction rates of the
other player and find the optimal strategy and update value function and optimal extraction rate
for this player. Similar scenario for player 2.
%input:
%q: other player extraction rate
%x1_max, x2_max: initial resource level
%n: number of grid nodes in each direction
%PN: player number (1 for player 1 and 2 for player 2)
%FN: function number: each number is related to a functional form
%h: time ahead
%tol: tolerance for value function
%v_01, v_02: value functions
%output
%optimal extraction rates
%v_01,v_02:updated value function

function [q  v_01 v_02]=q_feedback(q,x1_max,x2_max,n,PN,FN,h,tol,v_01,v_02)

options = optimset('Algorithm','interior-point','MaxFunEvals',10000000);



x1=linspace(0.000001,x1_max,n)';
x2=linspace(0.000001,x2_max,n)';
u=ones(n,n);
dif=1;



if PN==1                                % for player 1
    while tol<dif                       % until value function at this node converges
        for i=1:n                       % each (i,j) forms a different node of the grid
            for j=1:n

                x_l1=x1(i,1);           % resource of player 1 at node(i,j)
                x_l2=x2(j,1);           % resource of player 2 at node(i,j)
                q_l=q(i,j);             % q_l is player 2 extraction at node (i,j)

                [u(i,j),v_001(i,j)]= fminbnd(@F1,0,x_l1,options);% finding the optimal extraction
                                                                 % by maximize. the right hand side
                                                                 % of bellman



            end
        end
        dif=max(max(abs(v_001-v_01))'); % change in the value function from the previous iteration
        v_01=v_001;                      % updating the value function of player 1

    end

else                                    % for player 2

    while tol<dif                       % until value function at this node converges
        for i=1:n
            for j=1:n                   % each (i,j) forms a different node of the grid

                x_l1=x1(i,1);           % resource of player 1 at node(i,j)
                x_l2=x2(j,1);           % resource of player 1 at node(i,j)
                q_l=q(i,j);             % q_l is player 2 extraction at node (i,j

                [u(i,j),v_002(i,j)]= fminbnd(@F2,0,x_l2,options); );% finding the optimal
                                                                     % by maximize. the right hand
```

```
                                                                       % side of bellman




          end
      end
      dif=max(max(abs(v_002-v_02))'  % change in the value function from the previous iteration
      v_02=v_002;                    % updating the value function of player 2

  end


end

q=u;                                 % q is the updated optimum strategy for each player




%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%functions%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

  function f=F1(u)

      if FN==1
          f=-(h*u*(10-u-q_l-(10-.5*(x_l1))))+(.95)^h*interpole_2(x1,x2,v_01,[x_l1-h*u;x_l2-
h*q_l]);
      end

      if FN==2
          f=-(h*u*(10*exp(-u-q_l)-(10-.5*(x_l1))))+(.95)^h*interpole_2(x1,x2,v_01,[x_l1-h*u;x_l2-
h*q_l]);
      end
      if FN==3
          f=-(h*u*(5*(u+q_l)^-.4-(10-.5*(x_l1))))+(.95)^h*interpole_2(x1 ,x2,v_01,[x_l1-h*u;x_l2-
h*q_l]);
      end

  end





  function f=F2(u)

      if FN==1
          f=-(h*u*(10-u-q_l-(10-.5*(x_l2))))+(.95)^h*interpole_2(x1,x2,v_02,[x_l1-h*q_l;x_l2-
u*h]);
      end



      if FN==2
          f=-(h*u*(10*exp(-u-q_l)-(10-.5*(x_l2))))+(.95)^h*interpole_2(x1,x2,v_02,[x_l1-
h*q_l;x_l2-u*h]);
      end

      if FN==3
          f=-(h*u*(5*(u+q_l)^-.4-(10-.5*(x_l2))))+(.95)^h*interpole_2(x1 ,x2,v_02,[x_l1-
h*q_l;x_l2-u*h]);
      end
```

```
    end
```

%%%%%%%%%%%%%%%%%% interpolation function%%%%%%%%%%%%%%%%%%%%

% This function give the y value for the point x when the function values Y exist for all nodes specified by X1,X2

```
function z=interpole_2(X1,X2,Y,x)



a=length(X1);
b=length(X2);

if x(1,1)<=min(X1)
    x(1,1)=min(X1);
end

if x(2,1)<=min(X2)
    x(2,1)=min(X2);
end

i=max(find(X1<=x(1,1),1,'last'),1);
j=max(find(X2<=x(2,1),1,'last'),1);

if i==a
   i=i-1;
end
if j==b
   j=j-1;
end

l1=(X1(i+1,1)-x(1,1))/(X1(i+1,1)-X1(i,1));
l2=(X2(j+1,1)-x(2,1))/(X2(j+1,1)-X2(j,1));

yy1=l1*Y(i,j)+(1-l1)*Y(i+1,j);
yy2=l1*Y(i,j+1)+(1-l1)*Y(i+1,j+1);

z=l2*yy1+(1-l2)*yy2;
```

The following MATLAB codes correspond to the algorithm to find the open-loop equilibrium explained in 3.2.1.

```
clc

clear all
format long
w0=300;
tol=0.01;
X1=1;X2=1;
for fn=1:3                    % different functional forms
    for j=2:2:10              % initial resource of player 1
        for k=10              % initial resource of player 2

            w=w0;             % initial time horizon
            while (X1(:)>tol | X2(:)>tol)    % until the final resourse level
                                             % is less than tol
                X1_0=j;
                X2_0=k;

                xx=[X1_0;X2_0];% initial resource of players
                period=w;


                    [yy x1 x2 q1 q2]=Optimum3(xx,period,fn);

                    X1=x1;
                    X2=x2;
                    xx=yy;


                w=w+100        % increasing the final time
            end

        end

    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Optimum3 takes the initial resource of players and time horizon as input and export
extraction rates and reserve level of players. FN determines the profit function

function [x1 x2 q1 q2]=Optimum3(xx,year,FN)

h=0.1;
n=year/h;
dif_q=1;
e1=xx(1,1);
e2=xx(2,1);
tol=0.001

ip=[ones(n,1); -ones(n,1)];

options = optimset('Algorithm','interior-point','MaxFunEvals',10000000);

%to find the optimal extraction path in each iteration, each player maximizes
```

```
%the sum of profits, where the extraction of the other player is given.
%a1: the optimand, the first half is the reserve level. The second half of
%a1 is the extraction rate.
%ip: initial value
%are the 0atr5xes f6r0 the 0a5n 0at5ces
%BB: matrix for inequality constraint(q>0, x1>0, x2>0 , q<x1,x2)
%AD: matrix for equality constraint(q_t=x_t-1 - x_t)

Wn=[eye(n-1,n-1) zeros(n-1,n+1);zeros(n+1,n-1) zeros(n+1,n+1)];
C=[zeros(n,n) eye(n,n);eye(n,n) zeros(n,n)];
L1=[zeros(2*n-1,1) eye(2*n-1,2*n-1);0,zeros(1,2*n-1)];

A=Wn*(L1-eye(2*n,2*n)-h*C);
B=[zeros(n,n)  zeros(n,n);zeros(n,n) eye(n,n)];
D=[1, zeros(1,2*n-1);zeros(2*n-1,1), zeros(2*n-1,2*n-1)];

AD=[A;D];

BB=[-eye(n,n)  zeros(n,n) ;zeros(n,n) eye(n,n);-eye(n,n) -eye(n,n)];

q=ones(n,1);
q1=ones(n,1);
q2=ones(n,1);

i=1;
while  dif_q >tol
    if mod(i,2)==1                      %for player 1
        x0=e1;
        X0=[x0 zeros(1,2*n-1)]';
        XX0=[zeros(2*n,1);X0];
        [a1 pr1] = fmincon(@F,ip,BB,zeros(3*n,1),AD,XX0,[],[],[],options);
        s=reshape(a1,n,2);
        dif_q=max(max(abs(-s(:,2)-q1)))
        q=-s(:,2);                      %optimal extraction of player 1
        q1=-s(:,2);
        x1=s(:,1);                      %optimal reserve level

    else                                %for player 2
        x0=e2;
        X0=[x0 zeros(1,2*n-1)]';
        XX0=[zeros(2*n,1);X0];
        [a2 pr2]= fmincon(@F,ip,BB,zeros(3*n,1),AD,XX0,[],[],[],options);
        s=reshape(a2,n,2);
        dif_q=max(max(abs(-s(:,2)-q2)))
        q=-s(:,2);                      %optimal extraction of player 1
        q2=-s(:,2);
        x2=s(:,1);                      %optimal reserve level

    end
    i=i+1                               %changing player
end
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Functions %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

    function a=F(X)
         z=reshape(X,n,2);
         if FN==1
           a=(-sum(-z(:,2).*(10+z(:,2)-q+.5.*z(:,1)-10).*exp(-.05*(h*t+l*n*h))));
         end

         if FN==2
           a=(-sum(-z(:,2).*(10.*exp(z(:,2)-q)+.5.*z(:,1)-10).*exp(-.05*(h*t+l*n*h))));
         end

         if FN==3
           a=(-sum(-z(:,2).*(5*(q-z(:,2)).^(-.4)+.5.*z(:,1)-10).*exp(-.05*(h*t+l*n*h))));
         end

     end


v=[x1 q1 x2 q2];

end
```

Conclusion

The first two chapters of this dissertation contribute to the recent literature on the relation between subjective well-being and different aspects of environment. The empirical analysis in the first chapter shows the impact of daily variation of air pollution on individuals' well-being. The main result of this chapter is that after controlling for individuals' characteristics as well as local and seasonal fixed effects, the daily variation of air pollution has a statistically significant effect on individuals' self-reported well-being. This is the first study that investigates the relation between air pollution and subjective well-being in Canada. These results add to the literature on the valuation of air quality as a public good. In the so-called life satisfaction approach the coefficients of life satisfaction estimation are used to calculate the compensating differential or the marginal willingness to pay for an incremental improvement in air quality. This is equal to the average marginal rate of substitution between annual household income and air quality.

Based on the estimated coefficients in this study, the compensating differential for a change in pollution by half a standard deviation throughout the year is about 4.4% of the average Canadian annual household income. Using the marginal willingness to pay for air quality, it is shown that the cost of exceeding the allowed level for air pollution in some parts of Canada is substantial. The welfare costs of pollution obtained in this study can be used in evaluating costs and benefits of environmental regulations and policies to account for a more direct impact of air quality on individuals' well-being rather than through health effects, job losses and other possible impacts of environmental policies.

Chapter 2 is an empirical study on the impact from weather, as another aspect of the environment, on individuals' reported life satisfaction. This study extends the work of Barrington-Leigh (2009) by considering a larger cross-sectional data set. Another novelty of this study compared to Barrington-Leigh (2009) is that it estimates the model using a panel data set in addition to the cross-sectional data set. The main result of this study is that temporal weather variations have a statistically significant impact on satisfaction with life. This effect is captured in a number of different specifications. The results of estimating the model on different groups of individuals show that women and individuals with poor health condition are more affected by weather conditions. Concerning the effect of climate, the analysis of the cross-sectional data shows the impact from long term climate variables on life satisfaction. The results of this study add to the evidence that the changes in individuals' local environment are reflected in their reported life satisfaction. The results also demonstrate that the impact of daily weather changes on life satisfaction is negligible compared to the effect of major determinants of well-being such as employment and marital status.

In the first chapter of this thesis, the life satisfaction approach was used to establish a monetary valuation of pollution as a non-market good. The results of such an analysis can provide insight into the design and evaluation of public policies. In fact, one reason for the increasing popularity of subjective well-being measures have is that they can be integrated into design and implementation of public policies in different ways. The information derived from the analysis of subjective well-being data can help policymakers to achieve objective goals such as improvements in the productivity as well as education and health systems.

A part of my future research is to find the direct impact of various government policies on Canadians' well-being. Oishi et al. (2012) investigated the effect of progressive taxation on well-being using Gallup World Poll data for 54 countries and find an association between more-progressive taxation and higher levels of subjective well-being which is mediated by citizens' satisfaction with public goods, such as education and public transportation. Using the same surveys investigated in this thesis (CCHS and NPHS), it is interesting to study the relation between tax policies and well-being in a country such as Canada with different taxation systems across provinces.

Chapter 3 contributes to the literature on the oligopolistic competition among exhaustible resource producers. In this chapter, the focus is to extend a number of results in previous studies, which were derived analytically in a dynamic game framework, using numerical approaches. First, assuming economic resource depletion, the analysis in Salo and Tahvonen (2001) is extended to the case of iso-elastic market demand. The computation time to derive the feedback equilibrium can be improved by replacing the method used in Salo and Tahvonen (2001) with the collocation method. I also derive the open-loop equilibrium numerically under the assumption of economic depletion, and compare the phase diagrams and the time path of extraction with those in the feedback case. To obtain the open-loop equilibrium numerically, an algorithm that approximates the problem in a discrete and finite time horizon is suggested. The problem of resource extraction under economic depletion is also investigated assuming uncertainty in next period resource level. Exhaustible resource producers usually differ in terms of production costs. Following the analysis in the symmetric costs case, the implications of cost asymmetry for extraction rate and profits of resource producers are obtained.

By using numerical approaches, it is possible to extend the study of Benchekroun and Van Long (2006) on the effect of resource discovery on producers' profit by accounting for production costs. Confirming the results of Benchekroun and Van Long (2006), with a more elastic demand it is more plausible that the profit of some firms reduces with an increase in resource stock. However, with non-zero costs, the decrease in profit from adding more resources depends on the relative costs of production rather than the relative initial reserve of producers.

The numerical methods applied in this study can be effectively used to examine the generality of existing results in exhaustible resource games that were established analytically. For example, Benchekroun et al. (2010) study the impact of change in the stock of resource producers on their profit and on social welfare. Using numerical approaches to find the feedback equilibrium, it is possible to find the implication of resource change when one relies on the feedback instead of on the open-loop equilibrium. However, some adjustments of the numerical methods are necessary in order to account for the cartel-fringe case.

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