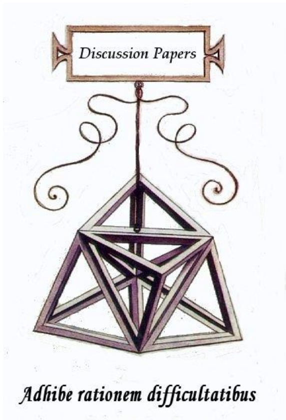
Discussion Papers
Collana di
E-papers del Dipartimento di Economia e Management – Università di Pisa



Tiziana Laureti

Life satisfaction and environmental conditions in Italy: a pseudo-panel approach

Discussion Paper n. 192

2014

Discussion Paper n. 192, presentato: **Dicembre 2014**

Indirizzo dell'Autore:
Dipartimento di Economia e Impresa, via del Paradiso 47, 01100 VITERBO – Italy
tel. (39 +) 0761 357821
fax: (39 +) 0761 357716
Email: laureti@unitus.it

Ringraziamenti

L'autore ringrazia Luca Secondi per il prezioso aiuto fornito nella costruzione del data set.

Si prega di citare così:
Laureti T. (2014), "Life satisfaction and environmental conditions in Italy: a pseudo-panel approach", Discussion Papers del Dipartimento di Scienze Economiche – Università di Pisa, n. 192 (http://www-dse.ec.unipi.it/ricerca/discussion-papers.htm).

Discussion Paper
n. 192

Tiziana Laureti

Life satisfaction and environmental conditions in Italy: a pseudo-panel approach

Abstract

This paper focuses on the relationship between subjective well-being and environmental conditions in Italy. Using a pseudo-panel approach, based on cohort data from the ISTAT multipurpose survey "Aspect of Daily Life" for the years 2010-2012, this paper aims at investigating the role of subjective and objective measures of environmental quality on life satisfaction by using fixed effects models taking into account regional heterogeneity and generational effects. A robust negative impact of air pollutions on self-reported life satisfaction is found. With respect to personal characteristics and control variables, the paper finds that the economic conditions and the perception of personal health status play important roles in explaining life satisfaction while car density, relative poverty risk and unemployment rates affect life satisfaction negatively.

Classificazione JEL: **C23 I31 Q53**
Keywords: environmental quality, subjective well-being, pseudo-panel

Contents

1. Introduction

In recent years economists have started employing subjective well-being as an empirical approximation to the notion of "experienced utility" (Kahneman et al 1997) with the aim of understanding individuals' preferences, testing existing theories, developing valuation studies of non-market goods and studying subjective poverty and inequality.

In this stream of literature, known as "happiness economics" and pioneered by Easterlin (1974), several studies have focused on the effects of factors directly related to the individual or the individual's household, such as personal and demographic characteristics, income and employment status, while others have analysed the role of factors related to the community and area in which the individual lives, such as inflation, social inequality and the role of political institution (for recent reviews see Stutzer and Frey, 2010; MacKerron, 2012).

One of the most important aspects related to the community is environmental quality, which is an important determinant of individuals' well-being and an important policy issue. Indeed, environmental conditions may affect people's sense of life satisfaction both directly, through impacts on the aesthetics and visibility of the local environment, and indirectly, through impacts on people's health, thus negatively influencing their ability to enjoy other aspects of their daily life. Individual life satisfaction may also be affected by their concern about environmental conditions.

More and more research studies focus on the empirical associations between subjective well-being and several dimensions of environmental quality such air quality (Welsh, 2002, 2006; MacKerron and Mourato, 2009; Ferreira et al. 2013), aircraft noise (Van Praag and Baarsma, 2005), climate (Rehdanz and Maddison, 2005), local amenities (Brereton et al, 2008), environmental attitudes (Ferrer-i-Carbonell and Gowdy, 2007) and natural hazards (Carroll et al 2009; Luechinger and Raschky, 2009).

The general idea is to model subjective well-being measures as a function of environmental features and socio-demographic factors, individuals' health status and economic conditions. In these studies, "subjective well-being" is considered as the overall assessment of each individual's life and is usually measured by carrying out surveys with questions concerning individual "happiness" or "life satisfaction" (van Praag et al, 2003).

Previous studies differ with respect to the methodological approach used which in turn depends on different assumptions regarding the subjective well-being measure considered in the analysis. Some authors adopt a micro approach thus using individual level data on subjective well-being, demographic and socio-economic characteristics together with location and time specific pollution data usually measured at a spatial aggregated level with few exceptions. On the contrary, other studies are based on the macro approach which uses an average subjective well-being measure as dependent variable and environmental and socio-economic features as covariates measured at national level.

The choice of the methodological approach often depends on the characteristics of the data available.

Panel or longitudinal survey data are particularly useful for analyzing subjective well-being and enable us to control individual heterogeneity (Ferrer-i-Carbonell and Frijters, 2004).

However, due to the high costs and the methodological issues that reduce the information obtained from panel samples, this type of statistical data is seldom available. On the other hand, cross-section surveys on life satisfaction are widely carried out on a regular basis resulting in an available series of independent cross-sectional data.

The aim of this paper is to use this kind of data by adopting a pseudo-panel approach (Verbeek, 2008) which enables us to effectively analyze the "environment-subjective well-being" relationship and to avoid unobserved heterogeneity and the danger of spurious correlation (Welsh, 2006).

Although repeated cross section data are not capable of following the same individuals over time there are certain advantages in using them rather than longitudinal data. Like all sample surveys, longitudinal surveys are affected by non-random attrition and the non-response in panel surveys tends to accumulate over time as further waves of interviewing are conducted (Watson and Wooden 2009). Moreover, in life satisfaction panel surveys, "panel conditioning" or ''panel effect'' represents a much debated current methodological issue, which implies that an individual's answers to questions depend on whether he/she has previously participated in the panel[1] (Chadi, 2013; Wooden and Li, 2014; Van Landeghem, 2012).

This paper contributes to literature by presenting new empirical evidence on the relationship between environmental quality and subjective well-being in Italy where so far few studies have been carried out on this topic (Laureti et al 2013). We used a pseudo-panel approach which is based on cohort data, defined in terms of the year of birth and region of residence of each individual

[1]The common finding is a negative trend in the data for life satisfaction (see for example Van Landeghem, 2012; Chadi, 2013).

and constructed from the annual Italian multipurpose survey "Aspect of Daily Life" carried out by the Italian National Statistical Institute (ISTAT).

Pseudo-panel models have become more and more popular over the last few years and are applied in various fields for carrying out a range of analyses such as transport demand (Dargay, 2007), cognitive achievement dynamics (De Simone, 2013) and poverty (Dang et al 2014). However, to the Authors knowledge, as yet pseudo-panel techniques have not been applied in the context of life satisfaction research.

This approach enables us to explore the relationship between life satisfaction and environmental quality by taking into account regional heterogeneity and generational effects. As the "Aspect of daily life" survey did not include questions concerning life satisfaction before 2010, our analysis is limited to the three-year period between 2010-2012.

Referring to the consolidated approach for assessing subjective well-being drivers (Frey and Stutzer, 2005; Helliwell, 2008), this paper aims at investigating the role of environmental characteristics on life satisfaction in Italy by using a fixed effects model. In addition to objective measures of environmental quality, we explore the role of self-reported assessments of environmental quality concerning local air quality and noise levels. Bearing in mind existing research, a large number of other explanatory variables are included to control for differences in the socio-economic characteristics of the Italian regions (Stutzer and Frey, 2010).

The rest of the paper is structured as follows. Section 2 introduces the theoretical frameworks and reviews the main studies in environmental economic literature concerning the impact of environmental conditions on subjective well-being. Section 3 illustrates the data used and the empirical implementation of the pseudo-panel approach. Section 4 presents the results and in the final section some conclusions are drawn.

2. Theoretical background

2.1 The use of subjective well-being measures in environmental economics

Data on subjective well-being are used in the ever-increasing literature concerning environmental economics, where subjective well-being measures are assumed to be a function of environmental amenities and socio-economic, demographic, and geographical information[2].

Subjective well-being data are collected through large-scale surveys by asking people to evaluate the quality of their lives (Helliwell, 2008).

The surveys are generally carried out annually. Each consecutive wave is based on a new, representative sample thus resulting in cross-sectional data. Panel surveys are carried out in few countries such as Germany, UK, US and

[2] In addition to standard methods of environmental valuation, the life satisfaction approach models individuals' self-rated well-being as a function of their incomes and the prevailing environmental conditions. This estimated relationship is used for obtaining the implicit marginal rate of substitution between income and the environmental characteristics in question (Welsch and Kühling, 2009).

Australia, where the same set of respondents is surveyed repeatedly on different dates, thus allowing for longitudinal studies. Some of the relevant surveys refer to single countries while others, such as the Eurobarometer Surveys and the World Values Surveys, use a common format for collecting subjective well-being measures in several countries.

Various questions have been asked with the aim of capturing overall life evaluations and global happiness including questions such as: “All things considered, how satisfied are you with your life as a whole these days?” or “Taking all things together, how happy would you say you are?”.

These questions capture different aspects of individual well-being (OECD, 2013). In particular, happiness is seen as a measure of particular feelings or emotional states (measures of *affect*) while conversely life satisfaction refers to a more cognitive and less transitory evaluation of well-being[3] (*evaluative* measures).

Despite earlier concerns, these measures appear to be relatively robust indicators of a person’s subjective well-being as individuals are able and willing to provide a meaningful answer when they are asked to evaluate their satisfaction level regarding their own lives on a finite scale (Ferrer-i-Carbonell, 2013). Indeed, there is now a large amount of literature underling the validity of subjective well-being measures and the fact that they contain substantial information on how individuals evaluate their lives[4] (Diener et al 2013).

Respondents usually report their life satisfaction or happiness on a numerical scale[5] (for example, from 0 to 10) or on a verbal scale[6] (for example, 4 or 7 points scale from “extremely unhappy” or “extremely dissatisfied” to “extremely happy” or “extremely satisfied”).

From a statistical perspective, there are important theoretical implications depending on whether the answers have a cardinal (equal-interval) or an ordinal meaning.

In the first case linear models can be used while discrete choice models should be applied for the latter. However, empirical studies found that treating data as cardinal or ordinal produced similar results when estimating the determinants of subjective well-being (Frey and Stutzer 2000; Ferrer-i-Carbonell and Frijters, 2004).

Most of the studies concerning the relationship between environment and subjective well-being differ according to the approach used for estimating the

---

[3] Subjective well-being can be defined as “Good mental states, including all of the various evaluations, positive and negative, that people make of their lives and the affective reactions of people to their experiences life satisfaction can also be measured in specific life domains such as family, health, and finances” (OECD, 2013). This definition encompasses three elements: Life evaluation – a reflective assessment on a person’s life or some specific aspect of it.; Affect – a person’s feelings or emotional states, typically measured with reference to a particular point in time. Eudaimonia – a sense of meaning and purpose in life, or good psychological functioning.

[4] Measures of subjective well-being have been longly and widely tested using various techniques and have been found to have a sufficient scientific standard in terms of internal consistency, validity, reliability

[5] In the World Values Surveys, interviewers are offered a scale from 1 (dissatisfied) to 10 (satisfied) to respond to the question: “All things considered, how satisfied are you with your life as a whole these days?”

[6] For example, in the Eurobarometer Surveys a four-point verbal life satisfaction scale is used to answer the question: “On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?”.

life satisfaction or happiness function which in turn depends on the structure of the survey data used. As already mentioned two main approaches were applied.

The micro approach uses individual level data often taken from cross sectional surveys, which may involve a single country (see for example Rehdanz and Maddison, 2008; Ferrer-i Carbonell and Gowdy, 2007 ; MacKerron and Mourato, 2009; Ferreira and Moro, 2010; Cuñado and Perez de Gracia, 2013) or several countries (Luechinger and Raschky, 2009; Ferreira et al, 2013; Silva et al, 2012) and occasionally panel surveys for each single countries (Carroll et al, 2009; Levinson, 2012).

The macro approach is usually based on average life satisfaction scores (by year and country) as dependent variable taken from cross sectional surveys involving various countries thus relying on a panel data setup (Welsh, 2002; Di Tella and MacCulloch, 2008; Luechinger, 2010; Maddison and Rehdanz, 2011).

When following the micro approach based and using cross sectional data, it is essential to control for heterogeneity in the individuals' characteristics such as their socio-demographic and socio-economic characteristics. However, there may be unobserved heterogeneity across individuals especially in respect to personality traits which may affect results substantially (Ferrer-i-Carbonell and Frijters, 2004)

The problem of unobserved micro heterogeneity may be addressed by aggregating across individuals thus following the macro approach. However, cardinality for the subjective well-being measures needs to be assumed when averaging happiness among individuals (Ferrer-i-Carbonell and Frijters, 2004).

Provided the data have an individual-panel structure, individual fixed effects models may be used to control for time-invariant unobserved influences on subjective well-being. However this condition is seldom fulfilled. Moreover individual panels may not remain representative over time and may be affected by non-random attrition and panel conditioning.

In this paper, we can overcome the heterogeneity issue as well as the non-availability of panel data on life satisfaction by using a pseudo-panel approach based on the cohort average data obtained from representative surveys over time.

2.2 Overview of the studies on the macro function linking subjective well-being and environmental quality

This section reviews the empirical applications of the macro approach by considering the environmental condition analysed and the data and methodological issues discussed above.

Most studies have focused on the effect of air quality measured by various pollutant emissions and climatic conditions using happiness or life satisfaction data taken from the World Database of Happiness.

The impact of air quality on self-reported well-being is analysed by Welsh (2002) who considered the average value of happiness, measured on a four-point verbal scale, for 54 countries, taken from the World Database of Happiness (Veenhoven, 2001) together with income and pollution data. With respect to the issue of measurement, Welsh (2002) obtained a continuous variable by assuming cardinality and used ordinary least squares techniques. It was observed that urban air pollution has a measurable effect on happiness expressed as a substantial monetary valuation of improved air quality.

The same source of data was used by Welsch (2006) to examine how self-reported well-being varies according to prosperity and ambient air quality. In order to control for unobserved between-country heterogeneity, he considered annual data taken from happiness surveys carried out in 10 European countries from 1990 to 1997 (Veenhoven, 2004) thus obtaining a panel of countries. The findings showed that air pollution plays a statistically significant role as a predictor of inter-country and inter-temporal differences in subjective well-being.

Menz and Welsch (2010) used an unbalanced panel of 136 observations in 25 OECD countries for 1990, 1995 and 2000-2004 obtained from the World Values Survey Series. They considered average values of life satisfaction measured on a four-point scale and estimated a fixed effect model with heteroscedasticity and autocorrelation robust standard errors. A negative relationship was observed between life satisfaction and air pollution, measured according to PM_{10} concentrations. The effect of air pollution on life satisfaction proved to be stronger for the young and the elderly than for middle-aged individuals.

With the aim of investigating whether and to what extent past air pollution affects the valuation of air quality, Menz (2011) used the same source of data on average life satisfaction scores regarding a set of 48 countries in the period from 1990 to 2006. The results indicate that habituation to air pollution is not of crucial importance in respect to the valuation of clean air. Indeed, lagged air pollution levels were negatively related to life satisfaction in the regressions.

In order to study the influence on subjective well-being caused by environmental degradation, assessed according to SO_x emissions, Di Tella and MacCulloch (2008) used data from the Euro-Barometer Surveys and the United States General Social Survey from 1975 to 1997. With the aim of including the U.S. data on happiness measured on a three-point scale the Authors transformed the four-category European answers for life satisfaction into three categories by merging the answers in the bottom two categories. They found that for a twenty-year-old individual the negative effect of SO_x emissions was two times higher than for a 70-year- old and that the negative effect was also observed in high income countries.

SO_2 pollution levels were also analysed by Luechinger (2010) who estimated their effect on life satisfaction for 13 European countries from 1979 to 1994 using data taken from the Euro-Barometer Surveys. He used OLS regressions and Probit adjusted OLS (POLS) regressions and found a statistically significant and robust negative effect of air pollution on life satisfaction.

A macro approach study of climate and happiness was carried out by Rehdanz and Maddison (2005) who used average happiness values for 67 countries (with 185 observations) between 1972 and 2000 obtained from the World Database of Happiness (Veenhoven, 2001). They therefore also assumed cardinality for happiness and control for between-country heterogeneity by using social and macroeconomic indicators. Using a panel-corrected least squares approach, they found that temperature has a highly significant effect on country-wide self-reported levels of happiness.

In a more recent paper Maddison and Rehdanz (2011) estimated the influence of climate on life satisfaction, measured on a 1–10 scale, using average data concerning 87 countries (with 178 observations) taken from the World Values Survey[7]. They found that countries with climates characterised by a large number of degree-months, calculated as the cumulated monthly deviations from a base temperature of 65 °F (18.3 °C), show significantly lower levels of life satisfaction.

Van der Vliert et al. (2004) examined how temperature affects nationally-averaged measures of happiness using data regarding 55 countries. It was observed that richer societies are happier while poorer societies are unhappier in hotter climates.

By using fixed effect models Carroll et al. (2009) estimated the cost of droughts by matching rainfall data with individual life satisfaction in Australia at post-code level in the period from 2001 to 2004 and it was found that droughts that occur in the springtime are associated with a large decline in life satisfaction for rural communities.

3. Data and Model design

3.1 Data sources and variable selection

The pseudo-panel data set was constructed from the annual Italian multipurpose survey "Aspect of Daily Life". This survey has been carried out annually by the Italian National Statistical Institute (ISTAT) since 1993 as part of an integrated system of social surveys - The Multipurpose Surveys on Household. Each year the "Aspect of Daily Life" survey involves a random sample of about 50,000 individuals (20,000 households) distributed in approximately 850 municipalities and collects detailed information on a range of topics regarding individual and household daily life.

Therefore the "Aspect of Daily Life" data set includes a large number of socioeconomic and demographic variables that enables us to assess the quality of citizens' lives, their economic situations, their state of health, the environmental characteristics of the area in which they live and the functioning of all public utility services. The variables used in the analyses and their definitions are shown in Table 1.

Starting from the 2010 survey, the question: "How satisfied are you with your life on the whole at present?" provided as with information on personal

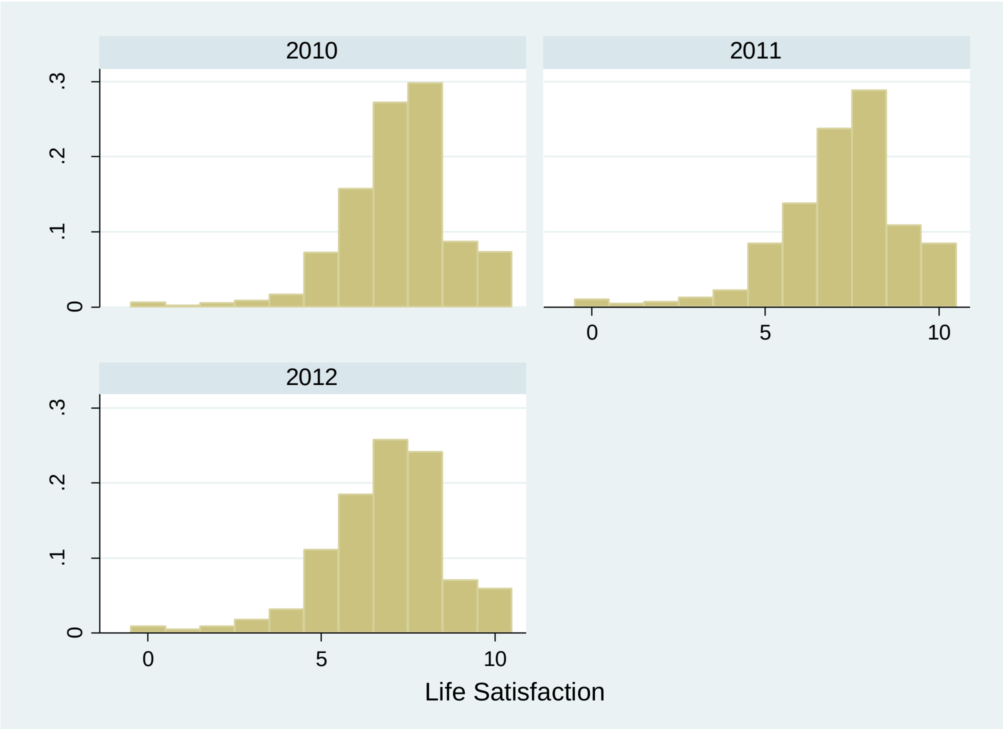
[7] They considered data obtained from surveys carried out over the period 1981–2008 (http://www.worldvaluessurvey.org/.)

overall life satisfaction. The respondents' answers are assessed by a numeric scale ranging from 0 (totally unsatisfied) to 10 (extremely satisfied).

It is worth noting that in 2010 approximately 97.2% of the respondents aged 18 years or over answered this question (39,083 individuals out of 40,211 individuals aged 18 or over) while this percentage rose to 98.1% in 2011 (38,963 respondents out of 39,729 individuals aged 18 or over). In 2012 approximately 98.2% of the respondents expressed their level of life satisfaction (37,962 individuals out of 38,751 individuals aged 18 or over).

As shown in Figure 1, the distribution of life satisfaction in Italy is negatively skewed in all the years under analysis ($skewness_{2010}$=-0.923, $skewness_{2011}$=-1.083, $skewness_{2012}$=-0.854).

Figure 1 Distribution of life satisfaction in Italy during the period 2010-2012.



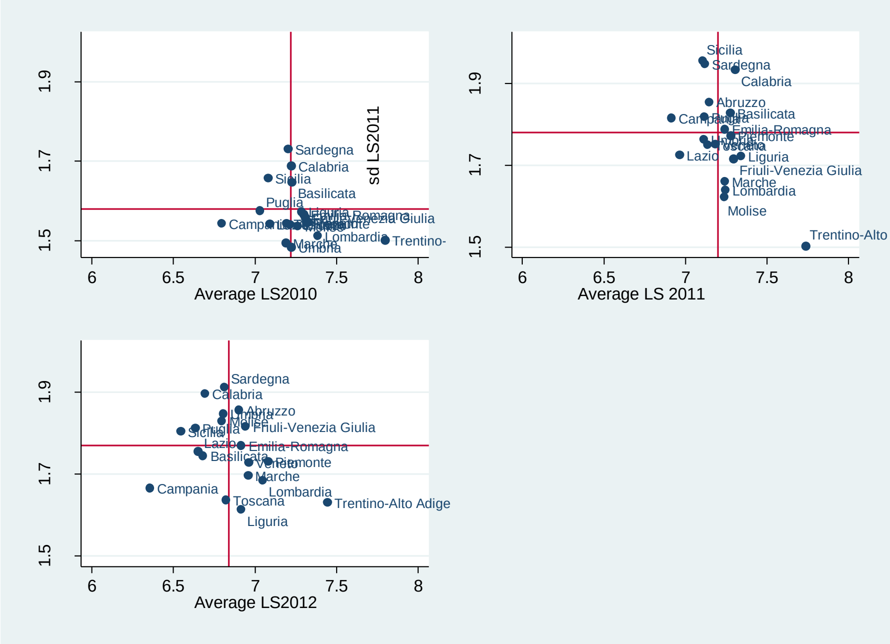
Italians are generally satisfied with their lives, although the economic crisis is negatively affecting the citizens' state of mind, behaviour and perception. In 2010 the percentage of individuals stating high levels of life satisfaction (with a score between 7 and 10) was equal to 73.15%. This value, which remained approximately the same in 2011 (72%), dropped to 63% in 2012.

The official sampling design of the ISTAT "Aspect of Daily Life" survey is implemented for producing reliable estimates only at regional level (NUTS 2).

Nevertheless, as shown in Figure 2, average life satisfaction in the Italian regions is characterized by a high level of heterogeneity, which has increased from 2010 to 2012.

In other words, there has been an increase in the gap in subjective well-being at territorial level over the last few years. Indeed, life satisfaction decreased more in the southern regions, such as Basilicata, Campania, Calabria, than in the northern regions, namely Liguria, Trentino Alto Adige and Lombardia, where the average value of life satisfaction was, and continued to be, above the average life satisfaction at national level until 2012.

Figure 2 Life satisfaction in the Italian regions: average value and standard deviation (2010-2012)



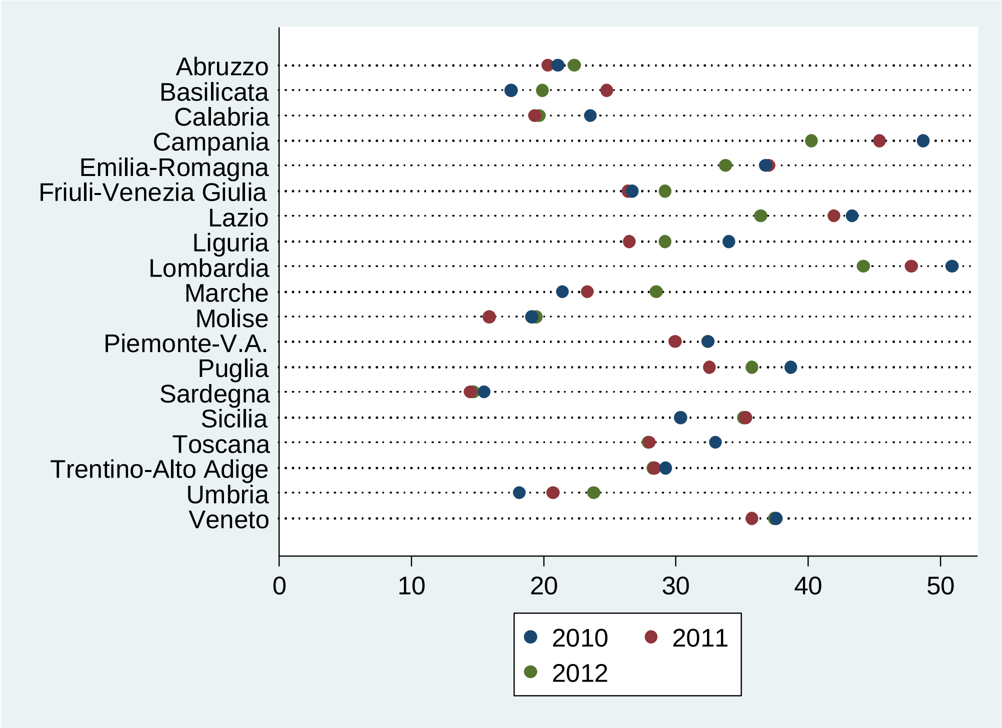
As we are able to match individual-level life satisfaction data with objective measures regarding environmental quality and socio-economic conditions only at regional level[8], we obtained measures of the pollution levels surrounding each respondent's residential area according to the extent to which an individual feels affected by air pollution or noise exposure. Indeed, in the "Aspects of Daily Life" survey, the respondents are asked to express their views concerning some of the environmental problems of the area in which they live by using an ordinal scale with five categories (None, Little, Some, A lot; I don't know).

We included other perceived indicators of the quality of urban environment such as the presence of dirt in the streets, unpleasant smells and availability of green areas (Rehdanz and Maddison, 2008).

Focussing on air pollution, Figure 3 shows the percentage of individuals declaring the presence of problems related to air quality (reporting "a lot or some" problems with air quality) across the Italian regions. It is worth noting that although this percentage in Lombardia, Campania and Lazio is still very high, it decreased from 2010 to 2012. On the contrary, although this percentage in Umbria and Marche is lower, the number of individuals complaining of air pollution increased over the same period of time.

[8] It is important to note that the "Aspect of Daily Life" survey considers Piemonte and Valle d'Aosta as one region.

Figure 3 Presence of air pollution (A lot/Some) in Italian regions (2010-2012)



With the aim of including objective indicators that account for the environmental conditions of the region in which the respondents reside we refer to data from the ISTAT Urban environmental quality and BES (Equitable and sustainable well-being) database regarding urban air quality, expressed as number of days per year that average daily PM10 concentration exceeds 50 mg/m3; availability of green areas, expressed in m2 per capita; car density, calculated as the percentage of cars in compliance with the euro-4 or higher standards; number of illegally-built homes for each 100 legally constructed.

Although individuals' perceptions of environmental quality were observed to be positively related to objective pollution measures (ρ=0.504 in 2012), various socio-economic and geographical factors may have a mediating effect on the relationship between measured and perceived conditions (Silva et al, 2012).

Therefore, we controlled for regional heterogeneity in socio-economic conditions by including the Gross Domestic Product (GDP) per capita, relative poverty risk, infant mortality rate, population density, unemployment rate, urbanization rates (Menz and Welsh, 2010; Menz, 2011).

In addition, we considered the socio-economic and socio-demographic characteristics of individuals which in previous studies were found to affect subjective well-being, such as gender, marital status, children, educational level, employment status, household economic status, home ownership, self-reported health status, suffering from chronic disease (see among others Ferrer-i-Carbonella and Gowdy, 2007; Levinson, 2012; Ferreira et al, 2013, Rehdanz and Maddison, 2008; Cuñado and Perez de Gracia, 2013; Ferreira et al, 2013).

Table 1 List of variables

Variable	Description	Source
Socio-demographic and socio-economic indicators Xijt		
Life satisfaction	0 (totally unsatisfied) -10 (extremely satisfied)	ISTAT "Aspect of Daily life"
Gender	Dummy: 1=female	
Age	Age of respondents in years	
Marital status	3 categories: never married, married, divorced/widowed	
Employment status	Dummy:1=employed	
Children	Dummy:1=number of children in the household	
Education	3 categories: Up to the middle school, Diploma, Degree/PhD	
Health status	5 categories: very bad, bad, quite (sufficiently) good, good, very good	
Suffering from chronic disease	Dummy:1=yes	
Judgment on the household economic resources	4 categories: excellent, adequate, poor, totally inadequate	
Comparison with economic situation of previous year	5 categories: much improved, a little improved, same condition, a little worse, much worse	
Took a holiday in the previous year	Dummy:1=yes	
Ownership of the house	Dummy:1=yes	
Environmental characteristics Zijt		
Dirt in the street	4 categories: none, little, some, a lot	
Air pollution	5 categories: none, little, some, a lot, I don't know	
Noise	5 categories: none, little, some, a lot, I don't know	
Unpleasant smells	5 categories: none, few, some, a lot, I don't know	
Availability of green areas	Dummy:1= if there is a park within walking distance	
Regional variables Wjt		
Urban Air Quality	Number of days per year that average daily PM10 concentration exceeds 50 mg/m3	ISTAT "Urban Environmental Quality"
Public green areas	m2 per capita	
Car density	Number of the motor cars circulating in the region complied with the euro 4 or higher standard per 1000 inhabitants	
Rate of illegally-built homes	Number of illegally-built homes for each 100 legally constructed	ISTAT BES
GDP per capita		
Relative poverty risk		

Variable	Description	Source
Infant mortality rate		
Unemployment rate		ISTAT
Density	Inhabitants per km-squared	
Urbanization	% of total regional population residing in urban areas	

3.2 The estimation of a linear fixed effect model of life satisfaction

Referring to literature, we assumed that the level of life satisfaction (LS) expressed by individual *i* in region *j* in year *t* is represented by the following function:

$$LS_{ijt} = \alpha_i + \boldsymbol{\beta}_1 \mathbf{X}_{ijt} + \boldsymbol{\beta}_2 \mathbf{Z}_{ijt} + \boldsymbol{\beta}_3 \mathbf{W}_{jt} + \varepsilon_{ijt} \qquad (1)$$

where $\mathbf{X}_{ij,t}$ is a vector of individual socio-demographic and economic characteristics, $\mathbf{Z}_{ij,t}$ includes self-reported assessments of environmental quality concerning local air quality and noise levels, $\mathbf{W}_{j,t}$ is a vector of variables aggregated at regional level describing the environmental characteristics and the socio-economic conditions of the regions where individuals reside, α_i is an individual-specific constant or fixed effect and ε_{ijt} is an error term.

In order to estimate an equation of this kind, life satisfaction data collected for the same individuals over time should be used which are not available in Italy. In fact, the available data set is a series of independent cross-sections, and therefore observations on N individuals are available for each year.

We suggest using a pseudo-panel approach[9] for estimating the fixed effect model (1). In this approach, introduced by Deaton (1985), individuals sharing some common characteristics, i.e. year of birth, are grouped into cohorts. The averages within these cohorts are then treated as observations in a pseudo-panel. This is equivalent to an instrumental variable approach where the grouping indicators are used as instruments (Veerbeck, 2008). If the cohorts are large enough, one can expect successive surveys to generate a series of random samples of individuals from each cohort.

Deaton's approach for estimating a fixed effect model using cohort means as observations was extended to nonlinear and dynamic models by Moffitt (1993) and Collado (1997) while alternative types of asymptotics was discussed by McKenzie (2004).

After having aggregated individuals into cohorts and computed averages for each cohort, the following model can be specified:

$$\overline{LS}_{ct} = \overline{\alpha}_{ct} + \boldsymbol{\beta}_1 \overline{\mathbf{x}}_{ct} + \boldsymbol{\beta}_2 \overline{\mathbf{z}}_{ct} + \boldsymbol{\beta}_3 \mathbf{w}_{jt} \varepsilon_{ct} \qquad c = 1,\ldots,C;\ t = 1,\ldots,T;\ j = 1,\ldots,J \qquad (2)$$

[9] An alternative strategy would be pooling all observations from repeated cross-sections and performing ordinary least squares treating $\alpha_i + \varepsilon_{ijt}$ as composite error term which produce consistent estimates only if the individual effects *i* are uncorrelated with the explanatory variables in x_{it}. However, the individual effects are likely to be correlated with some or all of the explanatory variables.

where $\overline{LS}_{ct}$ is the average value of all observed life satisfaction values in cohort *c* in period *t*, and similarly for the other variables in the model. The resulting data set is a pseudo-panel with repeated observations over T periods and C cohorts. We matched data on environmental quality and socio-economic conditions at regional level included in the vector $\mathbf{w}_{jt}$ to the pseudo-panel.

Since $\overline{\alpha}_{ct}$ may be correlated with $\overline{\mathbf{x}}_{ct}$ and $\overline{\mathbf{z}}_{ct}$, treating it as random may lead to inconsistent estimators. On the other hand, the fixed-effect framework is frequently used in life satisfaction literature (Carroll et al.2009)

On the other hand, the standard within estimator may be used for estimating model (2) if cohort averages are based on a large number of individual observations and therefore variation over time of $\overline{\alpha}_{ct}$ can be ignored. The properties of this estimator also depend on the way in which the cohorts are constructed. In particular, variables that do not vary over time and that are observed for all individuals in the sample should be used for defining cohorts.

These variables should satisfy the appropriate conditions for an instrumental variable estimator to be consistent. In other words, the instruments should be valid, thus being uncorrelated to the unobservables in the equation of interest, and relevant, that is, appropriately correlated to the explanatory variables in the model. The latter condition requires that cohorts are defined as groups whose explanatory variables change differentially over time.

For given cohort sizes, the bias in the within estimator, caused by the fact that the cohort observations are averages of the individuals included in each cohort[10], will be negligible if the cohorts are chosen so that the relative magnitude of the measurement errors is smaller compared to the within cohort variance of x_{ct} (Veerbeck, 2008).

Therefore, when constructing a pseudo-panel, there is a trade-off between the need to have a large number of observations per cohort and the desire to have as much informative data as possible. On one hand a larger number of cohorts and thus of data points increases the heterogeneity of the pseudo-panel by increasing the variations between groups, while it decreases the average number of individuals per cohort resulting in less precise estimates of the cohort means (Baltagi, 2005).

As shown by Verbeek and Nijman (1992) measurement error becomes negligible when cohort sizes are large (at least over 100 individuals) and the time variation in the cohort means is sufficiently large. Indeed, empirical researchers have generally not corrected for sampling error with group sizes of this magnitude (see among others Propper et al 2001; Dargay, 2007 and De Simone, 2013).

[10] Deaton (1985) treated this problem as a measurement error as cohort averages are error-ridden measures of true cohort averages and suggested a Fuller-type correction to ensure convergence of pseudo-panel estimates. However, Verbeek and Nijman (1993) showed that Deaton's estimator converges with the number of time periods.

3.3 Pseudo-panel construction and model specification

As already mentioned, our analyses used 3 years of repeated cross sections from 2010 to 2012, thus considering 117,775 individual observations, and followed the opinions of 7 birth cohorts in the 19 Italian regions considered in the “Aspect of Daily Life” surveys.

In order to ensure that the cohort means of the variables based on the sample are reasonable estimates of the population cohort variables, the construction of the pseudo-panel is based on the year of birth and the region in which the respondents reside. Specifically, we defined seven cohorts of age (1906-1933, 1934-1942,1943-1952, 1953-1962, 1963-1972, 1973-1982, 1983-1992) and considered the 19 Italian regions included in the ISTAT survey. For example, a first cohort is composed of all individuals aged between 18 and 27 in 2010 (and therefore born in period between 1983-1992) in region *j*. In 2011 this cohort will be aged between 19 and 28 and in 2012 the age of this cohort will range from 20 to 29. Other cohorts are constructed by considering all individuals aged 28-37 in 2010, those aged 38-47 and so on. In this way we construct a series of means of the variables reported in Table 1 considering those individuals who are members of the same birth cohort from 2010 to 2012.

Our choice of cohorts gives a balanced pseudo-panel of 7 cohorts, in 19 regions, over 3 years. The size distribution of each cohort can be seen in Table 2.

Table 2 Size Distribution of Cohorts- Average value

	Cohort age in 2010						
Region	**18-27**	**28-37**	**38-47**	**48-57**	**58-67**	**68-76**	**over 77**
Piemonte	384	567	679	614	560	448	330
Lombardia	354	545	642	545	485	350	248
Trentino-Alto Adige	279	344	467	375	329	233	165
Veneto	261	387	482	391	362	266	175
Friuli-Venezia Giulia	144	206	280	252	227	168	137
Liguria	149	202	290	263	250	211	207
Emilia-Romagna	218	305	412	344	314	226	207
Toscana	235	313	394	370	355	263	239
Umbria	134	192	224	188	177	135	140
Marche	193	260	289	268	241	200	163
Lazio	274	357	453	382	314	243	198
Abruzzo	211	233	303	271	213	178	165
Molise	162	177	217	218	160	146	143
Campania	496	508	593	496	423	287	211
Puglia	352	391	425	392	346	230	205
Basilicata	172	206	231	211	154	132	123
Calabria	289	322	372	323	273	188	179
Sicilia	390	445	478	449	387	269	213
Sardegna	218	269	326	298	265	168	132

4. Empirical Results

Several panel data estimations were carried out in order to compare the results across specifications and to identify the most robust specification. In all models cluster-robust standard errors are estimated (Table 3 and Table 4).

The first three columns of Table 3 show the coefficients of Eq. (2), estimated by pooled OLS, Random Effects (RE) and fixed effects (FE) estimators[11].

The null hypothesis of non-significance of the individual effects (cohort-specific effects) was rejected according to the F-test results (Table 3). Therefore, a common constant term for all the cohorts cannot be accepted and the pooled regression method is inappropriate. As the RE model can result in biased and inconsistent estimates if some of the explanatory variables are correlated with the specific effect or the error term, the standard and robust versions of the Hausman test were performed in order to detect the presence of this bias. The calculated Hausman test statistics reject the null hypothesis of no correlation between the individual effects and the regressors, suggesting that the RE estimates were biased. Therefore we estimated Eq.(2) using a fixed effect model, which enabled us to obtain interesting results concerning the effects of covariates on life satisfaction.

Table 3: Estimation results

	OLS			**FE**			**RE**		
	Coef.	Robust SE	Sig.	Coef.	Robust SE	Sig.	Coef.	Robust SE	Sig.
Gender	-0.3209	0.3620		0.3055	0.3082		-0.2929	0.3468	
Children	-0.1378	0.1703		-0.1824	0.2230		-0.1254	0.1693	
Education									
Diploma	-0.4704	0.2016	**	-0.3898	0.3124		-0.4749	0.2027	**
Degree/PhD	-0.8327	0.3057	***	-0.9970	0.4020	**	-0.9218	0.3152	***
Employment status	-0.1630	0.0993		0.2748	0.2542		-0.1477	0.0991	
Holiday in the previous year	0.5257	0.1712	***	0.6238	0.2469	**	0.5434	0.1721	***
Judgment on the household economic resources									
Poor	0.1439	0.5553		0.1043	0.5416		0.2219	0.5637	
Adequate	1.9401	0.6005	***	0.6674	0.5637		1.7460	0.5955	***
Excellent	4.5984	1.1077	***	3.0517	1.2046	**	4.5306	1.0466	***
Health status*(ref. very bad/bad)*									
quite good	2.4428	0.3076	***	2.5473	0.5162	***	2.3340	0.3127	***
good	1.7444	0.2165	***	1.6604	0.3961	***	1.6924	0.2291	***
very good	1.2942	0.2505	***	0.8435	0.4367	*	1.1731	0.2602	***
Environmental characteristics									
Dirt in the street *(ref. None)*									
Little	0.0711	0.2573		-0.2827	0.2441		-0.0363	0.2569	

[11] The estimation process was carried out using STATA 13.

	OLS			FE			RE		
	Coef.	Robust SE	Sig.	Coef.	Robust SE	Sig.	Coef.	Robust SE	Sig.
Some	0.6649	0.2869	**	-0.1557	0.2921		0.6707	0.2905	**
A lot	1.5870	0.4584	***	-0.2902	0.5353		1.3678	0.4552	***
Air pollution *(ref. None)*									
Little	-0.3571	0.3461		-0.3337	0.2983		-0.3640	0.3259	
Some	-1.3270	0.4035	***	-0.6378	0.3764	*	-1.1801	0.3770	***
A lot	-1.5892	0.5139	***	-0.9622	0.5674	*	-1.4486	0.5105	***
Noise *(ref. None)*									
Little	0.6910	0.3311	**	0.6345	0.2979	**	0.6785	0.3085	**
Some	0.7114	0.3976	*	0.5115	0.3114		0.6831	0.3726	**
A lot	1.7421	0.6282	***	0.9073	0.6460		1.7899	0.6332	***
Unpleasant smells *(ref. None)*									
Little	0.3223	0.3195		0.3398	0.2616		0.3136	0.2797	
Some	0.3944	0.3423		0.6766	0.3048	**	0.5482	0.3184	*
A lot	-0.3753	0.6208		0.2613	0.6063		-0.5358	0.5744	
Regional variables									
Availability of green areas	0.0937	0.2180		-0.3564	0.2553		-0.0050	0.2243	
Car Density	-1.0988	0.2595	***	-0.8557	0.2699	***	-1.0454	0.2551	***
Urban Air Quality	0.0012	0.0003	***	-0.0035	0.0007	***	0.0010	0.0003	***
Public green areas	0.0004	0.0001	***	-0.1481	0.0221	***	0.0004	0.0001	***
GDP per capita	0.0001	0.0016		0.0107	0.0048	**	-0.0014	0.0015	
Relative poverty risk	0.0064	0.0045		-0.0276	0.0052	***	0.0026	0.0045	
Infant mortality rate	-0.0019	0.0018		-0.0006	0.0020		-0.0021	0.0017	
Unemployment rate	-0.0525	0.0086	***	-0.1111	0.0098	***	-0.0629	0.0082	***
Rate of illegal homes	0.0023	0.0015		0.0172	0.0033	***	0.0030	0.0016	**
Urbanization	-0.2909	0.0681	***	4.5192	5.0956		-0.2586	0.0702	***
Population Density	-0.0004	0.0002	**	-0.0004	0.0004		-0.0005	0.0002	**
Intercept	5.1869	0.6512	***	14.2484	3.2224	***	5.8075	0.6542	***
F statistic for all α_i=0								3.82 ***	
Hausman test FE vs. RE								133.28***	

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Model 1 in Table 4 only includes the vector of individual socio-demographic and economic characteristics $\bar{\mathbf{x}}_{ct}$ while Model 2 also considers self-reported assessments of environmental quality concerning air pollution, noise levels, presence of unpleasant smells and dirt in the street ($\bar{\mathbf{z}}_{ct}$). Regional variables $\mathbf{w}_{j,t}$ describing the environmental characteristics and the socio-economic conditions of the regions in which the respondents reside are included in Model 3 (Table 4).

The results regarding the socio-economic and socio-demographic characteristics are more or less in line with results from previous studies, where gender appeared to be insignificant in life satisfaction regressions (see for example Frey and Stutzer, 2000). Employment status is positive and significant only in Model 2.

We found that the respondents with higher educational levels are less satisfied with life than those with lower educational levels as observed by Rehdanz and Maddison (2008). On the other hand, Cuñado and Perez de Gracia (2013) found a quadratic relationship between education and happiness. This result may suggest that more educated individuals tend to have higher expectations which are seldom satisfied due to the difficulties involved in finding a suitable position.

As in previous literature (Ferreira et al 2013; Cuñado and Perez de Gracia, 2013) the results in Table 4 indicate that people who report to be in good and very good health are substantially more satisfied with life than those in bad health.

Perceived air pollution is negative and statistically significant especially in Model 3 when regional environmental and socio-economic characteristics are introduced. Other subjective measures of environmental quality are not generally statistically significant (Rehdanz and Maddison, 2008).

We found a positive and significant coefficient for perceived noise (little) and unpleasant smells (some) in Models 2 and 3. These results, which require further analysis, may be due to the influence of various factors which can attenuate or compensate the effects of noise and unpleasant smells on life satisfaction. In order to explore these effects, in addition to individual-related variables, such as age, duration of noise and smell pollution, noise and smell sensitivity, other variables should be considered, such as house-related variables (floor level, number of windows oriented towards the source of noise and smells), and the characteristics of the sources of noise and smells (traffic, position of rubbish bins). It is worth noting that the few studies that have examined the effect of noise on life satisfaction (Van Praag and Baarsma, 2005 and Rehdanz and Maddison, 2008) found a negative relationship only for some of the model specifications considered, which may suggest that it is not such a strong effect.

Considering the objective indicators of environmental quality, the number of days per year that the average daily PM10 concentration exceeds the limit established for the protection of human health has a negative and statistically significant effect on life satisfaction, thus confirming previous findings in literature (Frijters and van Praag, 1998; Rehdanz and Maddison, 2005; Welsch, 2002, 2006).

The unexpected negative and significant effect of public green areas may be due to a shortcoming of the available data used. As already mentioned, the urban green space measure was the average of public green space, expressed in m2 per inhabitant at regional level. However, the available green surface area of parkland may not express quality accurately especially if it is not properly maintained. Moreover, previous studies that have examined the relationship between green spaces and life satisfaction used data at city level obtaining mixed results. While Ambrey and Fleming (2013) found a positive effect of public green space in the resident's district, Bertram and Rehdanz (2014) found that additional urban green space increases life satisfaction yet above a certain threshold a negative effect on life satisfaction is observed.

Considering control variables, we found that relative poverty risk and unemployment rates affect life satisfaction negatively, whereas urbanization and population density have no significant influence (Di Tella and MacCullogh, 2007; Menz and Welsh, 2010). Car density, measured according to the number of less polluting vehicles, has a negative effect on life satisfaction. This result indicates that car traffic is responsible for air pollution and other negative external factors such as noise pollution or traffic congestion.

Table 4: Estimation results: model specifications

	Model 1			Model 2			Model 3			Model 4		
	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.	Coef.	SE	Sig.
Gender	-0.3324	0.4827		-0.2370	0.4554		0.3055	0.3082		0.3671	0.3218	
Children	0.9047	0.3219	**	0.6704	0.3256	*	-0.1824	0.2230		-0.2806	0.2114	
Education												
Diploma	-1.1196	0.3895	**	-1.2094	0.3705	***	-0.3898	0.3124		-0.2271	0.2904	
Degree/PhD	-3.1719	0.5649	***	-3.2151	0.5541	***	-0.9970	0.4020	**	-0.7919	0.3654	**
Employment status	0.5448	0.3940		0.7510	0.3545	*	0.2748	0.2542		0.2420	0.2485	
Holiday in the previous year	1.8024	0.2973	***	1.6357	0.2975	***	0.6238	0.2469	**	0.4454	0.2323	*
Judgment on the household economic resources												
Poor	1.4455	0.7867		1.3954	0.7651		0.1043	0.5416		-0.1668	0.5088	
Adequate	3.3197	0.7627	***	3.2636	0.7589	***	0.6674	0.5637		0.2669	0.5251	
Excellent	6.6129	1.6856	***	7.1934	1.5207	***	3.0517	1.2046	**	2.0670	1.1065	*
Health status*(ref. very bad/bad)*												
quite good	0.8353	0.5856		0.7579	0.5857		0.8435	0.4367	**	0.6382	0.4538	
good	1.5338	0.5955	**	1.6307	0.5542	**	1.6604	0.3961	***	1.4784	0.4184	***
very good	1.5241	0.6757	**	1.8183	0.6888	**	2.5473	0.5162	***	2.4070	0.5288	***
Dirt in the street *(ref. None)*												
Little				-0.5705	0.3665		-0.2827	0.2441		-0.3204	0.2190	
Some				-0.0226	0.4443		-0.1557	0.2921		-0.1982	0.2787	
A lot				-1.4243	0.7626		-0.2902	0.5353		-0.4973	0.5111	
Air pollution *(ref. None)*												
Little				-1.0404	0.4240	*	-0.3337	0.2983		-0.0939	0.2975	
Some				-0.9927	0.4976		-0.6378	0.3764	*	-0.3658	0.3701	
A lot				-0.0308	0.8641		-0.9622	0.5674	*	-0.3949	0.5433	

Noise *(ref. None)*												
Little				1.0265	0.4300	*	0.6345	0.2979	**	0.6534	0.2979	**
Some				-0.0450	0.5266		0.5115	0.3114		0.2834	0.3117	
A lot				1.2551	0.9592		0.9073	0.6460		0.7763	0.6218	
Unpleasant smells *(ref. None)*												
Few				1.2388	0.3621	***	0.3398	0.2616		0.2052	0.2577	
Some				0.6695	0.4661		0.6766	0.3048	**	0.4773	0.2797	*
A lot				0.5870	0.8256		0.2613	0.6063		0.5101	0.5708	
Availability of green areas				-0.0321	0.3146		-0.3564	0.2553		-0.4531	0.2552	*
Car Density							-0.8557	0.2699	***	0.1386	0.4353	
Urban Air Quality							-0.0035	0.0007	***	-0.0033	0.0006	***
Public green areas							-0.1481	0.0221	***	-0.0799	0.0362	**
GDP per capita							0.0107	0.0048	**	-0.0087	0.0066	
Relative poverty risk							-0.0276	0.0052	***	-0.0203	0.0054	***
Infant mortality rate							-0.0006	0.0020		-0.0010	0.0019	
Unemployment rate							-0.1111	0.0098	***	-0.0653	0.0125	***
Rate of illegal homes							0.0172	0.0033	***	0.0086	0.0038	**
Urbanization							4.5192	5.0956		8.9833	5.2670	*
Population Density							-0.0004	0.0004		-0.0006	0.0004	
Year2011										0.0437	0.0404	
Year2012										-0.2174	0.0599	***
Cohort effect	YES			YES			YES			YES		
Intercept	2.8933	0.9107	**	2.9170	0.9040	**	6.6519	4.1036	*	5.2094	2.7937	*
R^2	0.506			0.5605			0.8104			0.8293		

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

5. Concluding remarks

Subjective well-being measures can provide another outlook concerning the positive or negative aspects of a community, as experienced by the citizens themselves. To this respect, concerns for environmental quality and the impact it may have on individual subjective well-being are important policy issues at community level.

In this paper we adopted a pseudo-panel approach with the aim of analysing the influence of environmental quality on life satisfaction. By using cohort average data obtained from representative surveys over time we can overcome the heterogeneity issue as well as the non-availability of panel data on life satisfaction.

The cohort data were defined in terms of the year of birth and region of residence of each individual and were constructed by using ISTAT "Aspect of Daily Life" repeated cross-section data from 2010 to 2012.

Bearing in mind that individuals living in the same region share some common characteristics and that their level of life satisfaction may be related to these specific regional characteristics, we matched data on environmental quality at regional level as well as information on socio-economic characteristics of the Italian regions to the pseudo-panel.

This enabled us to explore the relationship between individual life satisfaction and environmental conditions at regional level by also taking the age cohort effect into account (Blanchflower and Oswald, 2004 Frijters and Beatton, 2012).

Our results confirmed the findings of previous research studies suggesting that air quality, measured by means of both perceived and objective indicators, has a negative and significant impact on subjective wellbeing in Italy.

This suggests that environmental policies at regional level should be implemented in order to reduce air pollution with the aim of increasing the quality of urban environments thus positively influencing individual life satisfaction.

Interestingly we found that reported low levels of noise and unpleasant smells slightly increased life satisfaction. This is most likely due to the influence of house-related variables and the characteristics of the sources of noise and smells. Further research should include these variables which may compensate the effects of noise and unpleasant smells on life satisfaction.

The same methodological approach could be used in future analyses at more disaggregated territorial levels (i.e. provincial level) with the aim of examining the relationship between life satisfaction and environmental conditions measured according to objective indicators. It would also be interesting to include climate variables (such as temperature and precipitation).

References

Ambrey, C.L. and Fleming, C.M., 2013. Public Greenspace and Life Satisfaction in Urban Australia. *Urban Studies* DOI: 10.1177/0042098013494417.

Baltagi B.H. (2005) Econometric Analysis of Panel Data John, 3rd ed. Wiley & Sons Ltd, , West Sussex PO19 8SQ, England.

Bertram, C. and Rehdanz, K. (2014) The role of urban green space for human well-being, Kiel Working Paper, No. 1911.

Blanchflower, D.G. and Oswald, A. J. (2004) Well-being over time in Britain and the USA. *Journal of Public Economics* 88(7-8), 1359–1386.

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

Carroll N. Frijters P. and Shields M.A. (2009) Quantifying the costs of drought: new evidence from life satisfaction data, *J Popul Econ* 22 445–461

Chadi A. (2013) The role of interviewer encounters in panel responses on life satisfaction, *Economics Letter*, 121 550–554.

Collado, M.D. (1997), Estimating Dynamic Models from Time Series of Independent Cross-Sections, *Journal of Econometrics* 82, 37–62.

Cunado, J., and Perez de Gracia, F. (2013). Environment and happiness: New evidence for Spain. *Social Indicators Research* 112 (3) 549-567.

Dang H.A. Lanjouw P. Luoto J. and McKenzie D. (2014) Using repeated cross-sections to explore movements into and out of poverty, *Journal of Development Economics* 107 112–128.

Dargay J. (2007) The effect of prices and income on car travel in the UK, *Transportation Research Part A*, 41 949–960.

Deaton, A. (1985), Panel Data from Time Series of Cross Sections, *Journal of Econometrics* 30, 109–126.

De Simone G. (2013) Render unto primary the things which are primary's: Inherited and fresh learning divides in Italian lower secondary education, *Economics of Education Review* 35 12–23

Diener E., Inglehart R. and Tay L. (2013) Theory and Validity of Life Satisfaction Scales, *Social Indicators Research* 112, 497–527

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

Easterlin, R., (1974) Does economic growth improve the human lot? Some empirical evidence. In: David, P., Reder, M. (Eds.), Nations and Happiness in Economic Growth: Essays in Honor of Moses Abramowitz. Academic Press, New York, 89–125.

Ferrer-i-Carbonell, A. (2013) Happiness economics *SERIEs* 435–60

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

Ferrer-i-Carbonell, A., Gowdy, J.M. (2007) Environmental degradation and happiness. *Ecological Economics* 60 (3), 509–516.

Ferreira, S., Akay, A., Brereton, F., Cuñado, J., Martinsson, P., Moro, M., Ningal, T.F., (2013) Life satisfaction and air quality in Europe. *Ecological Economics* 88, 1–10.

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

Frey B.S. and Stutzer A. (2000) Happiness, Economy and Institutions *The Economic Journal Volume* 110 (466), 918–938

Frey B.S. and Stutzer A. (2005) Happiness Research: State and Prospects, *Review of Social Economy*, Vol. LXII, No 2.

Frijters P. and Beatton T. (2012) The mystery of the U-shaped relationship between happiness and age, *Journal of Economic Behavior & Organization,* 82 525– 542

Helliwell, J.F. (2008) Life satisfaction and quality of development. NBER Working Paper 14507. Cambridge: National Bureau of Economic Research.

Kahneman, D., Wakker, P., Sarin, R. (1997) Back to Bentham? Explorations of experienced utility. *Quarterly Journal of Economics* 112, 375–405.

Laureti T, Biggeri L, Secondi L (2013). Exploring well-being in Italy: the role of the environment. In: Measuring progress at a local level. Pisa University Press, ISBN: 978-88-6741-166-5.

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

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

Luechinger S. and Raschky P.A. (2009) Valuing flood disasters using the life satisfaction approach, *Journal of Public Economics* 93 620–633

MacKerron (2012) Happiness Economics from 35000 feet, *Journal of Economic Surveys* 26 (4), 705–735

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

McKenzie, D.J. (2004) Asymptotic Theory for Heterogeneous Dynamic Pseudo-Panels, *Journal of Econometrics*, 120, 235–262.

Maddison, D., Rehdanz, K. (2011): The impact of climate on life satisfaction, *Ecological Economics*, 70(12), 2437-2445.

Menz, T., (2011) Do people habituate to air pollution? Evidence from international life satisfaction data *Ecological Economics* 71 211–219

Menz, T., and Welsch, H. (2010). Population aging and environmental preferences in OECD countries: The case of air pollution. *Ecological Economics*, 69, 2582–2589.

Moffitt, R. (1993), Identification and Estimation of Dynamic Models with a Time Series of Repeated Cross-Sections, *Journal of Econometrics*, 59, 99–123.

OECD (2013) OECD Guidelines on Measuring Subjective Well-being, OECD Publishing.

Propper, C., H. Rees and K. Green (2001), The Demand for Private Medical Insurance in the UK: A Cohort Analysis, *The Economic Journal*, 111, C180–C200.

Rehdanz, K., & Maddison, D. (2005). Climate and happiness. *Ecological Economics*, 52, 111–125.

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

Silva, J., F. de Keulenaer and N. Johnstone (2012), Environmental Quality and Life Satisfaction: Evidence Based on Micro-Data, OECD Environment Working Papers, No. 44, OECD Publishing.

Stutzer, A. and Frey, B.S. (2010) Recent advances in the economics of individual subjective well-being, Discussion paper series // Forschungsinstitut zur Zukunft der Arbeit, No. 4850

Stutzer A. and Frey B.S. (2012) Recent developments in the economics of happiness: A selective overview, Discussion Paper Series, Forschungsinstitut zur Zukunft der Arbeit, No. 7078

Van de Vliert, E., Huang, X. and Parker P.M. (2004) Do colder and hotter climates make richer societies more, but poorer societies less, happy and altruistic? *Journal of Environmental Psychology* 24 17–30

van Praag, B. M. S. and Baarsma, B. E., (2005) Using happiness surveys to value intangibles: The case of airport noise. *The Economic Journal* 115 (500), 224–246.

van Praag, B., Frijters, P., and Ferrer-i Carbonell, A., (2003) The anatomy of subjective well-being. *Journal of Economic Behaviour and Organization* 51 (1), 29–49.

Van Landeghem, B. (2012). Panel conditioning and self-reported satisfaction: Evidence from International panel data and repeated cross-sections. SOEPpapers (on Multidisciplinary Panel Data Research) no. 484. Berlin: DIW.

Veenhoven, R. (2001) World database of happiness. http://www.eur.nl/fsw/research/happiness/.

Veenhoven, R. (2004) World Database of Happiness. www.eur.nl/ fws/research/happiness, September 16, 2004.

Verbeek M. (2008) Pseudo-panels and repeated cross-section in The Econometrics of Panel Data, Advanced *Studies in Theoretical and Applied Econometrics* Volume 46, pp 369-383.

Verbeek, M. and Th.E. Nijman (1992), Can Cohort Data Be Treated As Genuine Panel Data?, *Empirical Economics*, 17, 9–23.

Verbeek, M. and Th.E. Nijman (1993), Minimum MSE Estimation of a Regression Model with Fixed Effects from a Series of Cross-Sections, *Journal of Econometrics*, 59, 125–136.

Watson, N., & Wooden, M. (2009). Identifying factors affecting longitudinal survey response. In P. Lynn (Ed.), Methodology of Longitudinal Surveys (pp. 157–182). Chichester, UK: Wiley.

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

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

Wooden M. and Li N. (2014) Panel Conditioning and Subjective Well-being, *Social Indicators Research* 117, 235–255.