ECOLOGICAL ECONOMICS 65 (2008) 386–396

available at www.sciencedirect.com

ScienceDirect

www.elsevier.com/locate/ecolecon

ANALYSIS

Happiness, geography and the environment☆

Finbarr Brereton, J. Peter Clinch, Susana Ferreira*

University College Dublin, Richview, Clonskeagh, Dublin 14, Ireland

ARTICLE INFO

Article history:
Received 2 March 2007
Received in revised form 6 June 2007
Accepted 6 July 2007
Available online 29 August 2007

Keywords:
Subjective well-being
Spatial amenities
Geography
Environment
Geographical Information Systems

ABSTRACT

In recent years, economists have been using socio-economic and socio-demographic characteristics to explain self-reported individual happiness or satisfaction with life. Using Geographical Information Systems (GIS), we employ data disaggregated at the individual and local level to show that while these variables are important, consideration of amenities such as climate, environmental and urban conditions is critical when analyzing subjective well-being. Location-specific factors are shown to have a direct impact on life satisfaction. Most importantly, however, the explanatory power of our happiness function substantially increases when the spatial variables are included, highlighting the importance of the role of the spatial dimension in determining well-being.

1. Introduction

The economics of happiness literature developed in the early nineteen seventies with the pioneering work of such researchers as Richard Easterlin. Easterlin and subsequent authors, such as Daniel Kahneman, believe that individual utility, traditionally thought by economists to be immeasurable and hence proxied by income, can be measured directly. One method is to employ happiness data from surveys as empirical approximations of individual utility. The specific question asked varies throughout the literature in terms of subject matter (questions on happiness and life satisfaction are frequently employed) and range of scale (three-point to ten-point scales have been employed in the literature). These questions elicit happiness or life satisfaction from individuals and measures such as these have been found to have a high scientific standard in terms of internal consistency, reliability and validity (Diener et al., 1999)[1] and have been used extensively in the economics literature in recent decades (see, e.g., Easterlin, 1974; 1995; 2001, or Frey and Stutzer, 2000; 2002a,b; 2004).

This literature has examined the role of socio-economic and socio-demographic variables on individual well-being. Established findings within the field include that characteristics of the individuals themselves, their socio-demographic characteristics, such as their age, gender and marital status, influence their happiness. Similarly for micro-economic characteristics, such as income, household tenure and employment status, with unemployment having a profound negative influence on well-being. At the macro-economic level, contributions have focused on the impact of national inflation (Di Tella et al., 2001) and unemployment (Clark and

☆ Financial support of the Environmental Protection Agency ERTDI program is gratefully acknowledged.

* *Corresponding author*. Tel.: +353 1 716 2751; fax: +353 1 716 2788.
E-mail addresses: finbarr.brereton@ucd.ie (F. Brereton), peter.clinch@ucd.ie (J.P. Clinch), susana.ferreira@ucd.ie (S. Ferreira).

[1] Firstly, measures of life satisfaction show temporal reliability, even over a period of several years; secondly, they covary with ratings made by family and friends, with interviewer ratings and with amount of smiling in an interview; and finally, when self-reports of well-being are correlated with other methods of measurement, they show adequate convergent validity (Diener and Suh, 1999).

0921-8009/$ - see front matter © 2007 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecolecon.2007.07.008

Oswald, 1994) rates and also the type of governance present in the person's area (Frey and Stutzer, 2000). Happiness is found to be inversely related to the inflation and unemployment rates, but to increase with the level of direct democracy.

Prior literature in the economics field has demonstrated that the area or location where an individual lives affects quality of life. This is especially evident in the hedonic pricing literature where there is a long tradition of constructing quality of life indices as the weighted averages of amenities in a particular area, usually a city or region (see Rosen, 1974; Roback, 1982 or Blomquist et al., 1988, for seminal contributions, and Chay and Greenstone, 2005, for a recent state-of-the-art valuation exercise).[2]

However, it wasn't until the 1990s that researchers began to examine this spatial aspect of well-being in the economic psychology literature. These more recent papers found that characteristics of people's immediate surroundings (their locality) influenced their well-being, but also that the wider environment had an important role to play in explaining what makes us happy. Environmental variables such as aircraft noise (van Praag and Baarsma, 2005), air pollution (Welsch, 2002; 2006) and the prevailing climate (Frijters and van Praag, 1998 and Rehdanz and Maddison, 2005) are found to influence welfare, as are environmental attitudes (Ferrer-i-Carbonell and Gowdy, 2007). Findings indicate that excess noise levels adversely affect well-being, as does air pollution and the influence of climate depends on the variable in question, indicating the potential importance of spatial factors in determining well-being.

In terms of examining the geography of well-being, previous studies were hindered by a lack of adequately disaggregated data (Welsch, 2006; Rehdanz and Maddison, 2005). By the authors own admission, data constraints at the local and regional levels restricted their analysis to aggregated data at the national level, or to focusing on a particular localised area where richer data was available. Hence, thus far, the current literature has stopped short of carrying out a holistic study of the spatial element of well-being, due in no small part to these data constrains, but also to the lack of availability of appropriate tools to carry out such analysis. For example, Rehdanz and Maddison (2005) examine the influence on well-being of climatic conditions, but including too many of their climate variables in the model at once leads to problems of multicollinearity as some of their climate variables did not vary at the national level (i.e., one record per country). They state that their analysis was restricted to the country level and that it would be interesting to see how climate would affect people's happiness in different regions of a country. Ferrer-i-Carbonell and Gowdy (2007) include a set of dummy variables indicating the region where the individual lives to capture the (natural) environment, proxying, for example, London and Manchester as polluted areas. However, in the case of major cities in developed countries, pollution is, generally, a localised phenomenon and categorising an entire cities population under one pollution level may severely under or overestimate their exposure. Welsch (2006) uses life satisfaction scores to value air pollution in European countries, but includes no within country variation in his estimation. Due to a lack of data, Welsch's study was concerned with countries as the cross-sectional units and he states that "future research may address the question how regional or local happiness profiles are affected by the corresponding environmental conditions. It is conceivable that at a more disaggregated level the linkage between environment and happiness is even more articulate than it is with respect to national data". van Praag and Baarsma (2005) examine a localised problem and use postcodes to link their respondents to objective noise burden, but due to issues of anonymity, this application may only be available at city level where populations are aggregated.

In this paper, we explicitly endeavour to examine the importance of space in the determination of well-being, using a more holistic approach. Firstly, we measure amenities at the level of disaggregation at which individuals actually experience their surroundings, i.e. local level. This is facilitated through the use of Geographical Information Systems (GIS), a system for the visual display of spatial data. Using GIS, 1) the level of disaggregation at which individuals are linked to their surroundings is greatly improved; 2) the vector of spatial variables included in the happiness function is expanded to include variables with a potential influence on well-being, but which have not been examined to date; and 3) distance measures are introduced, as one could hypothesize that the intensity at which individuals experience their surroundings is a function of proximity (as in the case of air pollution and noise). The findings in the paper highlight the critical importance of the role of the spatial dimension in determining well-being, i.e., spatial variables are found to be highly significant with large coefficients. We also find that the impact of spatial amenities on life satisfaction is a function of distance, with the most notable example being that of proximity to coast. This has a large positive effect, which diminishes as one moves further from the coast. The results may have potentially important implications for the setting of public policy, e.g. decisions affecting the location of amenities negatively impacting on well-being, such as waste facilities. Most importantly, the explanatory power of our happiness function significantly increases when the spatial variables are included, resulting in three-times the variation in well-being being explained than has been achieved in any previous cross-sectional study. This indicates that geography and the environment have a much larger influence on well-being than previously thought.

The paper proceeds as follows. Section 2 describes the methodology (data, GIS requirements and the estimation strategy) used in the paper, Section 3 presents the results and Section 4 concludes.

[2] Roback (1982) found that the average person in her sample would be willing to pay $69.55 per year for an additional clear day, $78.25 per year to avoid an additional cloudy day, and $5.55 per year to avoid an increase of 1 μg per cubic meter in particulate matter. Blomquist et al. (1988) found that the difference in compensation between the most and least desirable U.S. counties in terms of the same bundle of local amenities comprising climate, urban conditions and environmental quality was $5,146. More recently, Berger et al. (2003) have shown that one standard deviation changes in climate attributes (heating degree days), air quality and crime produce annual compensation in the Russian housing and labor markets of 7,839, 8,050 and 8,602 rubles respectively, compared to a mean monthly salary of 1928 rubles.

2. Methodology

In this paper, we assume that the level of well-being attained by an individual i in location k can be represented by the following indirect utility function:

$$u_{i,k} = \alpha + \beta' \mathbf{x}_{i,k} + \gamma' \mathbf{a}_{i,k} + \varepsilon_{\mathbf{i,k}} \quad \mathrm{i} = 1....\mathrm{I}, k = 1, ..., \mathrm{K} \tag{1}$$

where u denotes utility of individual i in location k, **a** is a vector of spatial factors, some of which (e.g., commuting time, proximity to a coast) may vary at an individual level and $\boldsymbol{x}$ is a vector of socio-economic and demographic characteristics (age, gender etc.) that are typically included in the literature (see, e.g., Clark and Oswald, 1994; Di Tella et al., 2001 or Stutzer, 2004). In the micro-econometric function, the individual's true utility is unobservable, hence we use self-reported well-being as a proxy.

The well-being indicator (or proxy for individual utility) used in this paper is based on the answers to the following question (which was preceded by a range of questions regarding various aspects of the respondent's life): 'Thinking about the good and bad things in your life, which of these answers best describes your life as a whole?'. Respondents could choose a category on a scale of one to seven ('As bad as can be'; 'very bad'; 'bad'; 'alright'; 'good'; 'very good'; 'as good as can be').[3] The use of self-reported well-being introduces measurement error as the respondents may be unable to communicate accurately their underlying utility level. However, as Blanchflower and Oswald (2004a) point out, it is measurement error in the independent variables that would be more problematic in the econometric estimation, and there is a broad consensus among previous studies that self-reported well-being is a satisfactory empirical proxy of individual utility (see, e.g., Stutzer, 2004; Blanchflower and Oswald, 2004b; Ferrer-i-Carbonell and Frijters, 2004). Additionally, the use of a latent variable framework (i.e. Ordered Probit) controls for measurement error in the dependent variable.

Data on well-being and on the socio-demographic and socio-economic characteristics used in the analysis come from a survey[4] of a representative sample of 1,500[5] men and women, aged 18 and over and living in Ireland. The survey found a high well-being, in general, in Ireland with an average of 5.5 on the seven-point scale. What makes this data set particularly well suited for this paper is that it can be merged with detailed geographical information as we know the area in which the respondent lives. This information allows us to match the survey data spatially to a national map of Ireland using GIS and hence it is possible to combine subjective data at the individual level with a vector of spatial amenities (**a**).[6] These two datasets are combined at the local (electoral division)[7] level. However, to assess properly the impact on individual well-being from changes in spatial amenities, ideally, one would want to be able to match climate and environmental factors to a particular individual rather than a particular area. At present, however, the data do not allow this and anonymity may preclude this in any case. Descriptions of the variables and descriptive statistics are outlined in Appendix A.

The use of data collected in Ireland is interesting in its own right. In the last decade, the 'Celtic Tiger' economy grew at a record rate for a developed country (this and other trends are documented in, for example, Clinch et al., 2002). Meanwhile, the Economist Intelligence Unit (2004) has ranked Ireland as first in its quality of life league table for 2005. Nevertheless, there has been much concern regarding the implications of the pace of economic growth for localized environmental quality and life satisfaction generally (EPA, 2004). This makes Ireland an appropriate subject for the analysis of the influence of spatial amenities on subjective well-being. Furthermore, issues surrounding heterogeneity of preferences may not be as problematic in a small (approximately 70,000 km^2) and relatively homogenous country like Ireland, compared to other nations. Also, by examining one country, issues of translation and cultural bias in the well-being question should not arise.[8]

As elements of the vector of spatial factors, we include those variables which previous literature has shown to be important determinants of well-being. Roback (1982) includes the crime rate, population density and climatic conditions to construct Quality of Life indices for US cities using the hedonic pricing method. Blomquist et al. (1988) include similar variables in their analysis, also of US cities, but in addition they include the presence of waste facilities and proximity to coast. More recently, research in the economics of happiness has shown proximity to transport routes to affect well-being (van Praag and Baarsma, 2005).

The dataset contains climate (from Collins and Cummins, 1996), environmental (from EPA, 2005) and other spatial data (Urbis Database, 2006). Several climate variables were considered but following the advice of a climatologist, mean annual precipitation, January mean daily minimum air temperature, July mean daily maximum air temperature, mean annual duration of bright sunshine and mean annual wind speed

[3] Some studies treat self-reported life satisfaction data and happiness data interchangeably. Veenhoven (1997) states that "the word life-satisfaction denotes the same meaning and is often used interchangeably with happiness." Di Tella et al. (2001) report a correlation coefficient of 0.56. However, Peiro (2006) points to happiness and satisfaction as two distinct spheres of well-being. He concludes that the first would be relatively independent of economic factors while the second would be strongly dependent.

[4] Urban Institute Ireland National Survey on Quality of Life (2001).

[5] Due to missing observations the final sample consists of approximately (depending on the model specification) 1,467 observations. The effective response rate is 66.6%. The margin of error using the entire sample is ± 2.5% at a 95% confidence level. The 2000 Register of Electors was used as the sampling frame.

[6] GIS works well when applied to static data, and less well when applied to time series analysis (Goodchild and Haining, 2004) and hence is well-suited to the cross-sectional data employed in this paper.

[7] There are around 3,440 electoral divisions in Ireland which represent the smallest enumeration area used by the Irish Central Statistics Office in the collection of Census data. These areas are relatively small, particularly in the city regions and those represented in our sample range in size from 18ha (in cities) to 6,189ha (open countryside) (mean = 1,767, standard deviation = 1,538), with total populations ranging from 47 individuals to 8,595 (mean = 2,040, standard deviation = 2,073).

[8] However, the extent to which these biases are problematic is a matter of debate (Diener and Suh, 1999).

were chosen (similar to those included in Frijters and van Praag, 1998).

As in Blomquist et al. (1988), variables capturing whether the respondent lives near the coast, the violent crime rate and presence of waste facilities in the respondent's area were included. There is evidence suggesting that noise, smell and other negative externalities from waste facilities may impact negatively on well-being or quality of life (DG Environment, 2000). Air pollution and water quality were considered as indicators of environmental quality but regional variation is minimal (EPA, 2004). Additionally, population density (total population divided by total area in km^2 (CSO, 2003)), traffic congestion and average commuting time in each area were included to capture crowding and congestion effects. Also, a variable capturing voter turnout in the Irish general election in 2002 (Kavanagh et al., 2004) is included as an indicator for social capital (as in Putnam, 2000). Due to data constraints, traffic congestion (number of vehicles (DELG, 2002a,b) divided by the total length of primary roads per local authority[9] area (NRA, 2003)) and the homicide rate (number of homicides per 100,000 of population (Garda Siochana, 2002)) are measured at the local authority level.

As in van Praag and Baarsma (2005), we include proximity to airports.[10] However, we also include more detailed transport data consisting of proximity to: major roads (national primary and national secondary) (NRA, 2003); international, national and regional airports; railway stations, and seaports (Urbis Database, 2006). Access to transport routes could potentially enter the micro-econometric function in two ways, positively through accessibility and negatively through pollution and noise. The latter was shown to be the case by van Praag and Baarsma (2005) in relation to airport noise in Amsterdam.

As for the socio-economic and demographic variables, the dataset includes an employment-status variable divided into ten separate categories which follow the International Labour Organisation (ILO) classification: employed (self-employed, full-time employed and part-time employed), inactive (student, working on home duties, disabled, retired, those not working and not seeking work, and those on a government training scheme) or unemployed (CSO, 2006). Unemployment is further divided into two categories of those unemployed having lost or given up their job combined with those not working but seeking work, and those seeking work for the first time. Additional individual characteristics contained in the dataset and typically employed in the literature are age, gender, educational attainment (primary, lower secondary/junior high school, upper secondary/senior high school and university degree), marital status (single, married, cohabiting, widowed and separated/divorced), log of gross household income,[11] whether the respondent is caring for a disabled member of the family and the number of dependent children in the household (1, 2, 3+). As an indicator of individual health we use the number of times the respondent has visited the doctor in the past year (never or once, two to five times and six or more times a year). We also include household tenure (owned outright, mortgaged, renting, or in public housing).

2.1. *Geographical Information Systems methodology*

GIS is a powerful computing tool that allows the visual representation of spatially referenced data. It has advanced the technical ability to handle such data as countable numbers of points, lines and polygons[12] in two-dimensional space (Goodchild and Haining, 2004) and link various datasets using spatial identifiers (Bond and Devine, 1991). It represents a solid base for spatial data analysis and provides a range of techniques for analysis and visualisation of spatial data. It provides effective decision support through its database management capabilities, graphical user interfaces and cartographic visualisation (Wu et al., 2001).

2.1.1. *GIS in the economics literature*

Research using GIS in the economics field has tended to be in the area of environmental valuation through hedonic pricing and a new generation of hedonic studies is using GIS to create larger databases and define new explanatory variables in combination with spatial econometric methods (see Bateman et al., 2002; Lake et al., 1998). These hedonic models use a GIS programme to develop neighbourhood characteristics that are unique to each of their included observations (i.e. house or property). GIS has enhanced the ability of these hedonic models to explain variation in sale prices by considering both proximity to, and extent of, environmental attributes (Paterson and Boyle, 2002).

Baranzini and Ramirez (2005) use GIS to value the impact of noise in Geneva, while Lynch and Rasmussen (2001) use GIS to estimate the impact of crime on house prices in Jacksonville, Florida, USA. Paterson and Boyle (2002) use GIS data to develop variables representing the physical extent and visibility of surrounding land use in a hedonic model of a rural/suburban residential housing market. Bastian et al. (2002) use GIS data to measure recreational and scenic amenities associated with rural land, while Geoghegan et al. (1997) developed GIS data for two landscape indices and incorporated them in a hedonic model for Washington D.C, USA.

2.1.2. *Creating variables using GIS*

To capture accurately the influence of environmental and location specific variables on individual well-being requires variables to be measured at a high level of disaggregation i.e. at

[9] For governance purposes, Ireland is divided into 34 different regions called Local Authority areas. These generally equate to one body per county and one for the three major urban areas of Galway City, Limerick City and Cork City. Dublin is divided into four areas and Tipperary is divided into two local authority areas. These areas are relatively large and range in size from 2,035ha to 746,797ha (mean = 229,060, standard deviation = 226,508), with total populations ranging from 25,799 individuals to 495,781 (mean = 177,377, standard deviation = 135,990).

[10] All the proximity criteria are based on guidelines in Irish Government policy documents (see, DELG, 2002b).

[11] Income is expressed in thousands of euro. Missing values, 23.7% of those interviewed, were imputed based on the respondent's socio-demographic characteristics including age, gender, marital status, education level, area inhabited and employment status. The original income variable was divided in 10 categories, so mid-points were used (as in Stutzer, 2004). The survey was carried out when Ireland was still using the Irish Pound, so we converted to euros using the fixed rate of IR£1 = €1.26974.

[12] A polygon is the GIS term for any multi sided figure.

the level at which individuals experience their environment. Therefore they must be captured in a manner that reflects individuals' perceptions of the amenity or disamenity in question. Many facets of an amenity, such as intensity, frequency, duration, variability, time of occurrence during the day etc. (Bateman et al., 2001) will affect how an individual perceives the amenity. GIS allows variables to be related spatially and hence individuals can be linked to the geographic characteristics of their surroundings. Hence, GIS could, in principle, provide a full quantitative description of overall area quality if all relevant data layers, for example concerning road networks and public services, were available and were transformed in a convenient way into spatial attributes (Din et al., 2001).

However, when specific household or property GeoCodes (X, Y coordinates) are unknown, as in the case of the household survey data used in this paper, neighbourhood areas must be used as the reference point when creating environmental variables. The typical method of doing this is to use the mathematically-created centre or 'centroid' of the area in question[13] (as was the case in Craglia et al., 2001, who study high intensity crime areas in England) and in this paper we use the centroid of the respondents' electoral division. This introduces a maximum measurement error equal to the greatest distance between the centroid and the border of the electoral division in question which will be greatest in rural areas and smallest in the city regions.

The GIS requirements for this paper included the collection, assimilation and pre-processing of digital, spatial datasets, development of methods for spatio-temporal analysis and production of summary statistics and cartographic representations. This process produced layers of data which were 'mapped' into ArcView GIS. The data were entered into GIS as points (e.g. the location of waste facilities), lines (e.g. roads), or polygons (e.g. airports) within the categories of: meteorological; environmental; transport; and administrative boundary data layers. Different variables were entered in different ways. Some were entered directly as the spatial coordinates for this data were known, such as the airport co-ordinates. Others, such as the climate layers were entered as raster maps and these were converted to polygons for analysis purposes, as it was then possible to link individuals to characteristics of their areas. All data were converted to Irish National Grid co-ordinates.

Once the data layers were entered into the ArcView system, variables were created to allow statistical analysis to take place. For example, proximity to coast is measured as three dummy variables; less than two kilometres from the coast, between two and five kilometres and more than five kilometres. This allows us to examine if the amenity/disamenity values of the variables are functions of distance. We can also disaggregate between different types of similar amenities e.g. landfill and hazardous waste sites (EPA, 2005). Using proximity tools within ArcMap, distance 'buffers' were created from the centroid (as in Craglia et al., 2001) of each specific electoral division to a specified distance. Buffer analysis allows the researcher to take a point or line feature and generate a polygon containing all the area within a certain distance of the feature (Bond and Devine, 1991). A tool called 'select by location', was then used to identify the area where a particular environmental condition is satisfied. The variables created were either entered as columns of 0s and 1s, i.e. where the dummy equaled 1 for a particular electoral division if the condition was satisfied and 0 otherwise (e.g., 1 if an electoral division was within a 50 km radius of an airport and 0 otherwise) or as continuous variables (as in the case of the climate variables). These variables were then exported to the statistical software package STATA so econometric analysis could be carried out.

2.2. Estimation strategy

The stated aim of this paper is to examine the influence of space and place on individual well-being. As a first step towards capturing this influence, a micro-econometric happiness function is specified (Model 1) in which we distinguish between two distinct geographical areas of Ireland, i.e., between those respondents living in Dublin and those living in the rest of the country. This split was considered appropriate in a small (approximately 70,000 km^2) and relatively homogenous country like Ireland where the Dublin area comprises 28% of the population in only 1.3% of the land area, accounts for 39% of the national total of Gross Value Added and, with a population of 1.122 million, is the only urban area with a population in excess of 150,000. In Model 1, which also controls for a broad range of socio-economic and socio-demographic characteristics of the individuals in question (age, age-squared, gender, employment status, educational attainment, health, marital status, income, number of dependent children and household tenure), a dummy for Dublin might be seen as a rough summary measure of the amenities in that area. However, it does not provide much information regarding which specific amenities are most valued by the individuals. Therefore, in order to determine which site-specific factors are most relevant to well-being, a subsequent model is estimated (Model 2), corresponding to the estimation of Eq. (1), where the spatial variables equate to the amenities contained in vector **a**. This model contains the spatial amenities created using GIS and other data at the electoral division level.

Finally, because the regressions combine data at different levels of disaggregation (individual, electoral division and local authority levels), the standard errors in all the regressions are corrected for clustering (Moulton, 1990).

3. Results — assessing the importance of location

3.1. Model 1

Table 1 shows the results from the estimation of our models. Following the recent literature (e.g., Ferrer-i-Carbonell and Gowdy, 2007) and given the ordered nature of our dependent

[13] A 'centroid' is the mathematical term for the centre of an area, region, or polygon, calculated from points on its perimeter. In the case of irregularly shaped polygons, the centroid is derived mathematically and is weighted to approximate a 'centre of gravity.' These discrete X–Y locations are often used to index or reference the polygon within which they are located and sometimes attribute information is 'attached,' 'hung,' or 'hooked' to the centroid location.

Table 1 – Ordered probit regressions/dependent variable ‘life satisfaction’

Variable name		Model 1	Model 2
Age	Age	0.0188 (1.45)	0.0100 (0.74)
	Age-squared	−0.0002 (1.46)	−0.0001 (0.76)
Gender (female)	Male	−0.1665** (2.43)	−0.1719** (2.20)
Employment status (self employed)	Retired	0.0871 (0.54)	0.0350 (0.25)
	Engaged in home duties	−0.3941*** (3.22)	−0.2817** (2.19)
	Student	−0.1990 (1.13)	0.0251 (0.10)
	Seeking work for 1st time	−0.2090 (0.59)	−0.2061 (0.55)
	Unemployed	−0.9182*** (4.26)	−0.8674*** (3.94)
	Not working, not seeking work	−1.4317*** (3.95)	−1.4863*** (3.96)
	Working full-time	−0.1280 (1.26)	−0.0460 (0.50)
	Working part-time	−0.3695*** (2.80)	−0.2597* (1.82)
	Government scheme	−0.6624*** (2.61)	−0.9309** (2.54)
	Permanently unable to work	−0.4888 (1.61)	−0.6247* (1.94)
Education (primary)	Lower secondary/ junior high school	0.4210*** (3.68)	0.3023** (2.24)
	Upper secondary/ senior high school	0.1764* (1.69)	0.1940* (1.75)
	Degree	0.0617 (0.52)	0.1590 (1.15)
Health (visited the doctor 0 or 1 in the last year)	2–5 doctor visits	−0.1555** (2.46)	−0.2224*** (2.61)
	6 or more doctor visits	−0.3851*** (3.10)	−0.4252*** (3.04)
Marital status (single)	Married	−0.0138 (0.15)	0.0720 (0.74)
	Co-habiting	−0.1239 (0.83)	−0.2596 (1.18)
	Widowed	0.0880 (0.57)	0.1124 (0.69)
	Separated and divorced	−0.3762** (2.04)	−0.1981 (1.00)
Log income	Income (1000 s)	0.2103*** (2.90)	0.2649*** (2.95)
Number of children in the household (no children)	1 Child	0.0215 (0.20)	−0.1197 (0.93)
	2 Children	−0.0829 (0.87)	−0.1111 (1.09)
	3 or more children	−0.1772* (1.89)	−0.1838* (1.94)
Household tenure (own outright)	Own with a mortgage	−0.0194 (0.27)	0.0156 (0.20)
	Rent privately	0.0342 (0.27)	−0.0033 (0.02)
	Public housing	−0.5125*** (4.69)	−0.4781*** (3.61)

Table 1 (continued)

Variable name		Model 1	Model 2
Respondent is a carer		0.3314* (1.70)	0.2313 (1.24)
Dublin dummy variable		−0.7527*** (11.79)	−0.4430 (1.12)
Spatial variables		No	Yes
Climate variables	Precipitation		0.0005 (1.28)
	Wind speed		−0.3815** (2.36)
	January minimum temperature		0.8082*** (3.33)
	July maximum temperature		0.0806*** (3.85)
	Average annual sunshine (hours)		−0.0011 (1.22)
Average commuting time			0.0057 (0.48)
Population density			0.0061* (1.92)
Congestion			−0.0001 (1.17)
Homicide rate			0.0570 (0.97)
Voter turnout			0.0160* (1.84)
Proximity to landfill (more than 10 km)	Contains a landfill		−0.5145* (1.87)
	Within 3 km		0.4332 (1.55)
	Between 3 and 5 km		0.2998 (0.95)
	Between 5 and 10 km		−0.2359 (1.40)
Proximity to hazardous waste facility (more than 10 km)	Contains a hazardous waste facility		−0.4190 (0.71)
	Within 3 km		−0.1993 (0.54)
	Between 3 and 5 km		−0.3983 (1.01)
	Between 5 and 10 km		−0.2888 (0.89)
Proximity to coast (more than 5 km)	Within 2 km		1.1299*** (4.25)
	2 to 5 km		0.2761 (1.34)
Proximity to beach (more than 10 km)	Within 5 km		−0.2248 (0.73)
	Between 5 and 10 km		−0.1910 (0.62)
Proximity to rail station (more than 10 km)	Within 2 km		−0.2868 (1.28)
	Between 2 and 5 km		−0.3531 (1.37)
	Between 5 and 10 km		−0.0391 (0.14)
Proximity to airport (more than 60 km)			
Regional	Within 30 km		1.2726*** (2.63)
	Between 30 and 60 km		0.0543 (0.27)

(continued on next page)

Table 1 (continued)

Variable name		Model 1	Model 2
Proximity to airport (more than 60 km)			
National	Within 30 km		0.1404 (0.40)
	Between 30 and 60 km		0.5408 (1.55)
International	Within 30 km		0.4294 (1.56)
	Between 30 and 60 km		0.5371** (2.16)
Proximity to major road (more than 5 km)	Contains a major road		−0.6040** (1.97)
	Within 5 km		−0.5816* (1.79)
Proximity to sea ports (more than 10 km)	Within 3 km		−0.5826 (1.63)
	Between 3 and 5 km		0.0023 (0.01)
	Between 5 and 10 km		0.2877 (0.85)
Number of observations		1467	1464
Likelihood Ratio		−1845.59	−1692.85
Pseudo R^2		0.09	0.16

Note 1: *significant at 10% level; **significant at 5% level; ***significant at 1% level.
Note 2: *t*-statistics in parentheses computed using White's Heteroskedasticity-corrected standard errors.

variable, it contains results from ordered-probit regressions.[14] The reference groups for the independent variables are in parentheses.

The results on the socio-economic and socio-demographic characteristics in Model 1 are, broadly speaking, in line with previous findings in the economic psychology literature. For example, the coefficient on being unemployed is negative and significant and, everything else being equal, reduces life satisfaction substantially (see e.g., Blanchflower and Oswald, 2004a for similar results). Gender is significant and negative, indicating that males are less satisfied with their lives than females. Except for the study of Alesina et al. (2004) that finds gender to be significantly related to life satisfaction in the USA, in previous studies gender tends to emerge as insignificant in life satisfaction regressions (Stutzer, 2004; Frey and Stutzer, 2000; Di Tella et al., 2001). We find that those with lower (junior high school) or higher (senior high school) education are more satisfied with life than those with a primary education level (similar to Frey and Stutzer, 2000). As in Clark and Oswald (1994) and Blanchflower and Oswald (2004b), being separated or divorced is negative and significant. However, we find no difference between married and single respondents. Having three or more children is negative and significant at the 5% level (similar to Clark and Oswald, 1994). Respondents visiting their doctor two or more times a year are found to be less satisfied with life than those not attending or attending only once. Living in public housing is significant and negatively related to life satisfaction at the 1% level with a large coefficient. Perhaps surprisingly, being the carer of a disabled family member emerges as positive and significant in the regression. In line with the standard textbook prediction of utility as an increasing function of income, our proxy for utility (life satisfaction) is an increasing function of (log) income, which emerges significant at the 1% level. Age emerges insignificant in the regression. This is in contrast to the international literature which, generally, finds a U-shaped association between life satisfaction and age.

Examining the influence of location on well-being, we find the coefficient on the dummy variable for Dublin to be highly significant and large; only the coefficients for being unemployed and a discouraged worker are larger in magnitude. Everything else being equal, those living in all areas outside Dublin have a higher life satisfaction. This result is similar to that in Ferrer-i-Carbonell and Gowdy (2007), who find individuals living in Inner London to be less happy, everything else equal.

Having controlled for a large number of socio-economic and socio-demographic characteristics, a reasonable hypothesis is that factors related to the size of the settlement and other location-specific factors may be responsible for lower life-satisfaction levels in Dublin. For example, compared to any other area in the country, unparalleled growth rates have resulted in the capital having a much higher population density than other areas and a significant traffic congestion problem (DELG, 2002b). To test this hypothesis, Model 2 examines the importance of spatial amenities.

3.2. Model 2

Model 2, the results of which are reported in the last column of Table 1, corresponds to Eq. (1). It builds on Model 1 by including the variables with a spatial influence on well-being. These include population density, congestion, commuting time and the climatic and environmental variables. In this model, the dummy for Dublin loses its significance. This result suggests that the spatial variables explain an important part of the difference between living in Dublin and other regions of Ireland in terms of well-being.[15]

The pseudo-R^2 of Model 2, at 0.16, exceeds all those obtained to date in the international literature using a cross-sectional dataset. For example, Ferrer-i-Carbonell and Gowdy (2007) in their study of subjective well-being and environmental attitudes, obtain a pseudo-R^2 of 0.088. Another barometer of the explanatory power of the model is the adjusted-R^2 in Table 2 reporting the OLS results. The adjusted-R^2 increases from 0.21 in Model 1 to 0.33 in Model 2, which compares very favourably with those obtained in other studies; Stutzer (2004) for example, in his analysis of Swiss cantons, obtains an R^2 of 0.11. Since we control for similar socio-economic and demographic characteristics of the individual as in other studies of this nature, we believe this high adjusted-R^2 highlights the substantial influence of spatial amenities as determinants of well-being.[16]

[14] We also estimate OLS regressions (Table 2) and the results are comparable.

[15] We also estimate Model 2 without the Dublin dummy variable and the results are almost identical (results available on request from the authors).

[16] Additional R^2 obtained in the literature include Blachflower and Oswald (2004b) at 0.10, Di Tella et al. (2001) at 0.17 and Blanchflower and Oswald (2004a) at 0.084. However, these papers use pooled data over a number of years and hence, may not be directly comparable.

Table 2 – OLS regressions/dependent variable ‘life satisfaction’

Variable name		Model 1	Model 2
Age	Age	0.0155 (1.45)	0.0070 (0.70)
	Age-squared	−0.0002 (1.46)	−0.0001 (0.75)
Gender (female)	Male	−0.1369** (2.45)	−0.1232** (2.08)
Employment status (self employed)	Retired	0.0677 (0.52)	0.0407 (0.39)
	Engaged in home duties	−0.3142*** (3.17)	−0.1940** (2.00)
	Student	−0.1520 (1.06)	0.0149 (0.08)
	Seeking work for 1st time	−0.1706 (0.59)	0.0491 (0.21)
	Unemployed	−0.7810*** (4.17)	−0.6746*** (3.56)
	Not working, not seeking work	−1.1726*** (3.85)	−1.0821*** (3.60)
	Working full-time	−0.0994 (1.23)	−0.0306 (0.44)
	Working part-time	−0.3026*** (2.77)	−0.1628 (1.53)
	Government scheme	−0.5330** (2.48)	−0.6725** (2.39)
	Permanently unable to work	−0.4181 (1.61)	−0.4681* (1.82)
Education (primary)	Lower secondary/ junior high school	0.3331*** (3.50)	0.2038** (2.05)
	Upper secondary/ senior high school	0.1502* (1.68)	0.1284 (1.47)
	Degree	0.0582 (0.58)	0.0914 (0.87)
Health (visited the doctor 0 or 1 in the last year)	2–5 doctor visits	−0.1348** (2.53)	−0.1720*** (2.63)
	6 or more doctor visits	−0.3149*** (3.04)	−0.3249*** (3.07)
Marital status (single)	Married	0.0030 (0.04)	0.0671 (0.91)
	Co-habiting	−0.0696 (0.55)	−0.1435 (0.87)
	Widowed	0.0773 (0.61)	0.0945 (0.78)
	Separated and divorced	−0.3193* (1.93)	−0.1537 (0.93)
Log income	Income (1000 s)	0.1722*** (2.93)	0.2164*** (3.49)
Number of children in the household (no children)	1 Child	0.0160 (0.18)	−0.0920 (0.96)
	2 Children	−0.0828 (1.02)	−0.1204 (1.49)
	3 or more children	−0.1620** (2.06)	−0.1653** (2.24)
Household tenure (own outright)	Own with a mortgage	−0.0061 (0.10)	0.0149 (0.25)
	Rent privately	0.0309 (0.30)	0.0100 (0.08)
	Public housing	−0.4379*** (4.81)	−0.3594*** (3.52)

Table 2 (*continued*)

Variable name		Model 1	Model 2
Respondent is a carer		0.2632* (1.73)	0.2371* (1.91)
Dublin dummy variable		−0.6222*** (11.43)	−0.2434 (0.78)
Spatial variables		No	Yes
Climate variables	Precipitation		−0.0003 (1.05)
	Wind speed		−0.2459** (2.13)
	January minimum temperature		0.5558*** (3.19)
	July maximum temperature		0.0543*** (3.77)
	Average annual sunshine (hours)		−0.0011* (1.74)
Average commuting time			0.0034 (0.41)
Population density			0.0038 (1.63)
Congestion			−0.0001 (1.36)
Homicide rate			0.0501 (1.06)
Voter turnout			0.0124** (2.12)
Proximity to landfill (more than 10 km)	Contains a landfill		−0.3736* (1.90)
	Within 3 km		0.2646 (1.32)
	Between 3 and 5 km		0.2564 (1.05)
	Between 5 and 10 km		−0.1346 (1.07)
Proximity to hazardous waste facility (more than 10 km)	Contains a hazardous waste facility		−0.2068 (0.47)
	Within 3 km		−0.1715 (0.64)
	Between 3 and 5 km		−0.2998 (1.03)
	Between 5 and 10 km		−0.1560 (0.66)
Proximity to coast (more than 5 km)	Within 2 km		0.8351*** (4.32)
	2 and 5 km		0.2271 (1.51)
Proximity to beach (more than 10 km)	Within 5 km		−0.1607 (0.73)
	Between 5 and 10 km		−0.0923 (0.42)
Proximity to rail station (more than 10 km)	Within 2 km		−0.1705 (1.07)
	Between 2 and 5 km		−0.2271 (1.22)
	Between 5 and 10 km		−0.0142 (0.07)
Proximity to airport (more than 60 km)			
Regional	Within 30 km		0.8329*** (2.78)
	Between 30 and 60 km		0.0284 (0.21)

(continued on next page)

Table 2 (*continued*)

Variable name		Model 1	Model 2
National	Within 30 km		0.0721 (0.28)
	Between 30 and 60 km		0.3383 (1.44)
International	Within 30 km		0.2603 (1.30)
	Between 30 and 60 km		0.3851** (2.18)
Proximity to major road (more than 5 km)	Contains a major road		−0.3703* (1.83)
	Within 5 km		−0.3543 (1.62)
Proximity to sea ports (more than 10 km)	Within 3 km		−0.3887 (1.42)
	Between 3 and 5 km		0.0019 (0.01)
	Between 5 and 10 km		0.2054 (0.75)
Number of observations		1467	1451
Adjusted R^2		0.21	0.33

Note 1: * significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Note 2: *t*-statistics in parentheses computed using White's Heteroskedasticity-corrected standard errors.

Of the climate variables, the coefficient on mean annual precipitation is positive indicating that, for Irish people, increased rainfall slightly increases life satisfaction. This result may, however, be driven by a positive correlation between rain and scenic beauty.[17] The most spectacular landscapes in Ireland are found in the wettest counties in the West of Ireland. Rehdanz and Maddison (2005) find very scarce precipitation reduces happiness, which they hypothesize might reflect the fact that climate could have an indirect effect on happiness through landscape effects. However, in our case the coefficient emerges insignificant at conventional levels. Increases in the January minimum and July maximum temperatures emerge as amenities and increase life satisfaction. Wind speed emerges negative and significant in our regression, while surprisingly, we find that total annual sunshine is negatively related to life satisfaction. However, it may be that this result is driven by the correlation between elements of rainfall not captured in our variable (e.g., intensity and frequency) and sunshine.

As in the hedonic literature (e.g., Blomquist et al., 1988), we find the presence of waste facilities in an individual's area to be a disamenity. However, the type of, and distance from, the waste facility in question matters. The coefficient on the variable capturing if a landfill site is in operation in the respondent's electoral division emerges negative and significant compared to those who live in electoral divisions more than ten kilometres away. There is evidence suggesting that noise, smell and other negative externalities from waste facilities of this kind may impact negatively on well-being or quality of life (DG Environment, 2000). Proximity to landfill sites has been the subject of many hedonic analyses, such as Blomquist et al. (1988) who use the number of landfill sites per capita as a variable to construct Quality of Life indices, also Nelson et al. (1992) and Havlicek (1985) who examine the price effects of landfills on house values in US cities. Proximity to a hazardous waste facility however, does not seem to have an influence in terms of life satisfaction. It may be that individuals are less aware of the presence of these facilities in their areas. The coefficient on population density is positive and significant at the 10% level. This result is similar to that of Roback (1982), who finds population density to be an amenity. Average commuting time and congestion emerge insignificant in the regression as does the crime rate.

Proximity to coast emerges positive and significant with a large coefficient, indicating that individuals living near the coast enjoy higher life satisfaction, other things being equal. Additionally there is evidence that the utility value of coast is a function of distance with respondents living two kilometres or less from the coast more satisfied with their lives, compared to those living more than five kilometres from the coast. Those living between two and five kilometres from the coast are also more satisfied, if insignificantly so, but the coefficient is reduced. Interestingly, proximity to beach emerges insignificant in the regression. It may be that, given Ireland's climate, the amenity value of coastal areas is not a function of the availability of a beach.

We find access to transport emerges as both an amenity and disamenity, depending on the type of, and distance from, the amenity in question. Life satisfaction is highest for those living between thirty and sixty kilometres from an international airport. It may be that those less than thirty kilometres away are affected by the noise disamenity. In relation to regional airports, the amenity value lies at less than thirty kilometres. This result is not unexpected as these are small airports and only deal with smaller, less noisy aircraft and would have significantly fewer arrivals and departures than do the larger airports. Close proximity to a major road (less than five kilometres) emerges as a disamenity, again with distance decay. This may be capturing the noise affects of this transport route. Close proximity to a seaport emerges insignificant in the regression.

4. Conclusion

In this paper we adopt a holistic approach to the examination of the influence of geography and the environment on happiness. Using GIS we are able to overcome many of the difficulties that have prevented previous researchers addressing this issue comprehensively. This is achieved by matching individuals to their surroundings at a higher level of disaggregration and by expanding the vector of spatial variables included in the happiness function. We also use proximity measures to examine if the influence of spatial amenities on life satisfaction is a function of distance.

The findings show that climate has a significant influence on well-being, with wind speed negative and significant, but increases in both January minimum temperature and July maximum temperature are positive and significant. Access to major transport routes and proximity to coast and to waste facilities all influence well-being. However, the manner in which

[17] A high correlation coefficient is observed between precipitation and presence of Natural Heritage Areas (0.5874), the latter being EU-designated areas of outstanding natural beauty.

they enter the happiness equation differs depending on the amenity in question. Proximity to landfill is found to have a negative affect on well-being. Proximity to coast has a large positive effect, but its influence is a diminishing function of distance. Additionally, the impact of proximity to major transport routes has different effects depending on the type of, and distance to, the amenity in question, e.g., while reasonable proximity to international airports increases well-being, close proximity to major roads decreases it. It may be that, in the former case, the positive effect of access outweighs the negative effect of noise, while the opposite may be true in the latter case. These results may have potentially important implications for the setting of public policy, such as the location of waste facilities, the routing of major roads, location of airports etc., so as to have as minimal negative impact as possible on well-being.

Our findings highlight the critical importance of the role of the spatial dimension in determining well-being, i.e., spatial variables are found to be highly significant with large coefficients. In fact, the explanatory power of our happiness function substantially increases when the spatial variables are included, resulting in three-times the variation in well-being being explained than has been achieved in any previous cross-sectional study. This indicates that geography and the environment have a much larger influence on well-being than previously thought, as important as the most critical socio-economic and socio-demographic factors, such as unemployment and marital status. This finding has potentially important implications for setting priorities for public policy as, in essence, improving well-being could be considered to be the ultimate goal of public policy.

Acknowledgements

We thank Andrew Oswald, Michael Hanemann, Mirko Moro, Alan Carr and two anonymous referees for helpful comments. We thank Daniel McInerney and Sean Morrish for technical assistance. The usual disclaimer applies.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.ecolecon.2007.07.008.

REFERENCES

Alesina, A., Di Tella, R., MacCulloch, R., 2004. Inequality and happiness: are Europeans and Americans different? Journal of Public Economics 88, 2009–2042.

Baranzini, A., Ramirez, J.V., 2005. Paying for quietness: the impact of noise on Geneva rents. Urban Studies 42 (4), 633–646.

Bastian, C.T., McLeod, D.M., Germino, M.J., Reiners, W.M., Blasko, B.J., 2002. Environmental amenities and agricultural land values: a hedonic model using geographic information systems data. Ecological Economics 40, 337–349.

Bateman, I.J., Jones, A.P., Lovett, I.R., Day, B.H., 2002. Applying Geographical Information Systems (GIS) to environmental and resource economics. Environmental and Resource Economics 22, 219–269.

Bateman, I., Day, B., Lake, I., Lovett, A., 2001. The effect of road traffic on residential property values: a literature review and hedonic price study. Scottish Executive Transport Research Series. The Stationary Office, Edinburgh.

Berger, M.C., Blomquist, G.C., Sabirianova, P.K., 2003. Compensating Differentials in Emerging Labour and Housing Markets: Estimates of Quality of Life in Russian Cities. IZA Discussion Paper No, 900. October.

Blanchflower, D.G., Oswald, A.J., 2004a. Well-being over Time in Britain and the USA. Journal of Public Economics 88, 1359–1386.

Blanchflower, D.G., Oswald, A.J., 2004b. Money, sex and happiness: an empirical study. Scandinavian Journal of Economics 106 (3), 393–415.

Blomquist, G.C., Berger, M.C., Hoehn, J.P., 1988. New estimates of quality of life in urban areas. American Economic Review 78 (1), 89–107.

Bond, D., Devine, P., 1991. The role of geographic information systems in survey analysis. The Statistician 40 (2), 209–216.

Chay, K.Y., Greenstone, M., 2005. Does air quality matter: evidence from the housing market. Journal of Political Economy 113 (2), 376–424.

Clark, A.E., Oswald, A.J., 1994. Unhappiness and unemployment. Economic Journal 104, 648–659.

Clinch, J.P., Convery, F., Walsh, B.M., 2002. After the Celtic Tiger: Challenges Ahead. O'Brien Press, Dublin.

Collins, J.F., Cummins, T. (Eds.), 1996. Agroclimatic Atlas of Ireland: Working Group on Applied Meteorology. University College Dublin, Ireland.

Craglia, M., Haining, R., Signoretta, P., 2001. Modelling high-intensity crime areas in english cities. Urban Studies 38 (11), 1921–1941.

CSO, 2003. Census 2002: Population Classified by Area, volume 1. Central Statistics Office, Dublin.

CSO, 2006. Quarterly National Household Survey. Central Statistics Office, Dublin. Feb.

DELG, 2002a. Irish Bulletin of Vehicle and Driver Statistics. Stationary Office, Dublin. Dec.

DELG, 2002b. The National Spatial Strategy 2002–2020. Stationary Office, Dublin. Dec.

Diener, Ed., Suh, M.E., 1999. National differences in subjective well-being. In: Kahneman, D., Diener, E., Schwarz, N. (Eds.), Well-being: The Foundations of Hedonic Psychology. Russell Sage Foundation, New York.

Diener, E.D., Suh, E.M., Lucas, R.E., Smith, H.L., 1999. Subjective well-being: three decades of progress. Psychological Bulletin 125, 276–302.

Din, A., Hoesli, M., Bender, A., 2001. Environmental variables and real estate prices. Urban Studies 28 (11), 1989–2000.

Di Tella, R., MacCulloch, R.J., Oswald, A.J., 2001. Preferences over inflation and unemployment: evidence from surveys of happiness. American Economic Review 91, 335–341.

DG Environment, 2000. A Study on the Economic Valuation of Environmental Externalities from Landfill Disposal and Incineration of Waste, Final Main Report, European Commission, Brussels October.

Easterlin, R.A., 1974. Does economic growth improve the human lot? In: David, Paul A., Reder, Melvin.W. (Eds.), Nations and Households in Economic Growth: Essays in Honor of Moses Abramovitz. Academic Press, New York.

Easterlin, R.A., 1995. Will raising the incomes of all increase the happiness of all? Journal of Economic Behaviour and Organisation 27, 35–47.

Easterlin, R.A., 2001. Income and happiness: towards a unified theory. Economic Journal 111, 465–484.

Economist Intelligence Unit's Quality of Life Index, 2004. The Economist, London.

EPA, 2004. Ireland's Environment. Environmental Protection Agency, Wexford.

EPA, 2005. National Waste Database. Environmental Protection Agency, Wexford.

Ferrer-i-Carbonell, A., Frijters, P., 2004. How important is methodology for the estimates of the determinants of happiness? Economic Journal 114 (497), 641–659.
Ferrer-i-Carbonell, A., Gowdy, J.M., 2007. Environmental degradation and happiness? Ecological Economics 60 (3), 509–516.
Frey, B.S., Stutzer, A., 2000. Happiness, economy and institutions. Economic Journal 110, 918–938.
Frey, B.S., Stutzer, A., 2002a. Happiness and Economics. Princeton University Press, Princeton.
Frey, B.S., Stutzer, A., 2002b. What can economists learn from happiness research? Journal of Economic Literature 40 (2), 402–435.
Frey, B.S., Stutzer, A., 2004. Stress that Doesn't Pay: The Commuting Paradox. IZA Discussion Paper No, 1278.
Frijters, P., van Praag, B.M.S., 1998. The effects of climate on welfare and well-being in Russia? Climate Change 39, 61–81.
Garda, S., 2002. Annual Report. Garda Siochana, Dublin.
Geoghegan, J., Wainger, L.A., Bockstaell, N.E., 1997. Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. Ecological Economics 23, 251–264.
Goodchild, M.F., Haining, R.P., 2004. GIS and spatial data analysis: converging perspectives. Papers in Regional Science 83, 363–385.
Havlicek Jr., J., 1985. Impacts of solid waste disposal sites on property values. In: Tolley, G.S., Havlicek Jr., J., Favian, R. (Eds.), Environmental Policy: Solid Waste, vol IV. Ballinger, Cambridge. MA.
Kavanagh, A., Mills, G., Sinnot, R., 2004. The geography of Irish voter turnout: a case study of the 2002 general election. Irish Geography 37 (2), 177–186.
Lake, I.R., Lovett, A.A., Bateman, I.J., Langford, I.H., 1998. Modeling environmental influences on property prices in an urban environment. Computer, Environment and Urban Systems 22 (2), 121–136.
Lynch, A.K., Rasmussen, D.W., 2001. Proximity, neighbour and the efficiency of exclusion. Urban Studies 41 (2), 285–298.
Moulton, B.R., 1990. An illustration of a pitfall in estimating the effects of aggregate variables on micro units. Review of Economics and Statistics 72 (2), 334–338.
Nelson, A.C., Genereux, J., Genereux, M., 1992. Price effects of landfills on house values. Land Economics 68 (4), 365–395.
NRA, 2003. National Route Lengths. National Road Authority, Dublin.
Paterson, R.P., Boyle, K.J., 2002,. Out of sight, out of mind? using GIS to incorporate visibility in hedonic property value models. Land Economics 78 (3) , 417–425.
Peiro, A., 2006. Happiness, satisfaction and socio-economic conditions: some international evidence. Journal of Socio-Economics 35, 348–365.
Putnam, R.D., 2000. Bowling Alone: The Collapse and Revival of American Community. Touchstone, New York.
Rehdanz, K., Maddison, D., 2005. Climate and happiness. Ecological Economics 52, 111–125.
Roback, J., 1982. Wages, rents and the quality of life. Journal of Political Economy 90 (6), 1257–1278.
Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. Journal of Political Economy 82, 34–55.
Stutzer, A., 2004. The role of income aspirations in individual happiness. Journal of Economic Behaviour and Organization 54 (1), 89–109.
Urban Institute Ireland National Survey on Quality of Life, 2001. Urban Institute Ireland, Dublin.
Urbis Database, 2006. Urban Institute Ireland, Dublin.
van Praag, B.M.S., Baarsma, B.E., 2005. Using happiness surveys to value intangibles: the case of airport noise. Economic Journal 115, 224–246.
Veenhoven, R., 1997. Advances in the understanding of happiness. Revue Québécoise de Psychologie 18 (2), 29–74.
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.
Wu, Y.-H., Miller, H.J., Hung, M.-C., 2001. A GIS-based decision support system for analysis of route choice in congested urban road networks. Journal of Geographical Systems 3, 3–24.