SPATIAL HETEROGENEITY IN WELL-BEING

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Abstract

Self-reported measures of health and well-being have increasingly been proposed to make comparisons among countries or geographical regions and ranking quality of life. Such studies typically neglect the effect of spatial heterogeneity and reference scale differences among respondents. If one wants to improve interpersonal and country comparability, adequate empirical techniques must be adopted. We propose a microeconometric technique which enables us to control for different forms of spatial heterogeneity. Spatial heterogeneity may affect the *true* value of well-being via differences in local environmental attributes or may affect *reported* well-being via spatial differences in the reference scales used by respondents when collapsing their satisfaction or happiness into a given ordinal scale. We use data from a SWB survey conducted in Ireland to show that in certain cases differences in reference scale may be large even in small countries. We control for a large set of individual and location-specific environmental amenities matching a Geographic Information Systems data set with our survey data. The results show that environmental amenities have a positive effects on well-being, suggesting that environmental policies are unambiguously well-being enhancing. However, environment explains spatial heterogeneity of well-being up to a level. Differences in well-being across locations arise from different reference scales. For instance, those living in the metropolitan area of Dublin have reference points that are consistently lower than that of an average individual by 8-13%, while people living in more rural areas, such as the West of Ireland, has a reporting bias 1.30-1.75 times higher than the average. The conclusion is that environment and reference scale should be accounted for when comparing subjective well-being across locations and, even more important, across different countries.

Keywords: subjective well-being; heterogeneity; reference scale; reporting bias; generalized models; environment.

JEL classification: I31, C23

1. Introduction

Until recently, economists have been reluctant to use subjective measures of utility. In recent years, however, they have begun using subjective measures of well-being (SWB)

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as a proxy for utility, resulting in a rapidly growing "economics of happiness" literature.[1] Self-reported life satisfaction or happiness scores have been shown to depend on economic variables, such as income (see Clark et al., 2007 for a comprehensive overview; Easterlin, 1973; 1974 for early works); unemployment, which has been shown to have a marked negative impact (see, e.g., Clark and Oswald, 1994; Di Tella et al., 2001; Theodossiou, 1998; Winkelmann and Winkelmann, 1998); inflation (see, e.g., Di Tella et al., 2001, 2003); inequality (Alesina et al., 2004); and, more recently, on environmental variables such as air pollution (Welsch, 2002, 2006), climate (Frijters and Van Praag, 1998; Rehdanz and Maddison, 2005) and location-specific amenities (Brereton et al., 2007).[2]

A key underlying assumption in the economics of happiness literature is that SWB scores are good proxies for utility. Specifically, it is claimed that individuals are capable of evaluating their well-being with certain precision. Psychologists have been using self-reported well-being scores since the 1970s and there is an extensive literature providing evidence of a strong correlation between SWB scores and the underlying concept of utility. According to this literature, SWB indexes are reliable, consistent over time and valid (see, e.g., Clark et al., 2007; Di Tella and MacCulloch, 2006; Diener et al., 1999; Helliwell, 2006).

Another important issue when dealing with self-assessed indicators such as life satisfaction or self-reported health is that of interpersonal or cross-country comparability. Countries such as Ireland, Denmark and the Netherlands consistently rank highly in comparison with countries like Italy, France, Germany and Portugal in European or World surveys. For example, as reported in Kahneman et al. (2004), 64 percent of Danish respondents described themselves as "very satisfied" with their lives in a Eurobarometer survey, against only 16 percent of French respondents. As they convincingly argue, these differences appear questionably large, and they raise doubts about the validity of global reports of SWB and in cross-country comparability. These issues are even more important because some authors have invoked the introduction of national well-being

[1] As is common in the literature, the terms subjective well-being, life satisfaction, happiness and individual quality of life are used interchangeably in the remainder of the paper.
[2] For recent reviews see Frey and Stutzer (2002a; 2005) or Di Tella and MacCulloch (2006).

accounts as complements (and sometimes as alternative) to conventional national accounts (see for instance Ng, 1997; Oswald, 1997; Vemuri and Costanza, 2006).

A given level in the life-satisfaction scale could be interpreted differently by different people according to individual characteristics and their cultural, historical, geographical and national context. For example, people in more conformist or traditional environments tend to consult norms for whether they should be satisfied and to consider family and friends in evaluating their lives, or people in places where happiness ranks high as value are more inclined to overstate their appreciation of life.

Evidence that happiness scores are interpersonally comparable comes from experiments and from *ad-hoc* interviews conducted by psychologists where individuals are found to be capable to predict the feelings of their peers (see, e.g., Diener and Lucas, 1999; Sandvik et al., 1993). However, the data typically used in the literature to infer correlations between SWB and the covariates of interest, come from large surveys where the happiness question is one of the many questions being asked. When panel data are used an important form of unobserved heterogeneity, which is time-invariant such as personality traits, can be taken into account by using, for example, individual nuisance parameters (see, e.g., Ferrer-i-Carbonell, 2005; Ferrer-i-Carbonell and Frijters, 2004). The problem is more acute with cross-sectional data because respondents are not followed over time and individual heterogeneity cannot be controlled for.

In an attempt to control for other forms of heterogeneity, researchers typically estimate the effects of variables of interest on SWB including location fixed effects (country-specific dummies or regional dummies) as additional covariates to account for regional differences in environmental amenities and other omitted factors that vary at the regional level (see, e.g., Frey and Stutzer, 2000; Videras and Owen, 2006; Welsch, 2002).

However, a better empirical model that allows for differences in the reference scale of SWB is needed. Space may affect well-being trough alternative channels. First, differences across locations or countries could be explained by a different level of environmental quality, which is not typically controlled for when comparing happiness among regions or countries. Second, and more worrisome, differences in SWB among countries such as Denmark and Portugal may depend on differences in reporting styles instead of differences in 'true' well-being. Respondents living in different locations or countries may use different thresholds when collapsing their well-being in the ordinal scale provided in the happiness questionnaires, even if they experienced the same level of latent true well-being. [3]

In particular, spatial heterogeneity may affect the SWB reference scale in two ways. The regional effects may be the same on every level of SWB, so that all the thresholds are shifted by the same amount in a parallel fashion (index shift), or may be more flexible, in the sense that every threshold is affected in a different way by the region of residence (cut-point shift) (see Lindeboom and van Doorslaer, 2004). Because of this, (location or individual) fixed effects, typically included in cross-section or panel data econometric models, fail to fully capture spatial heterogeneity.

In this paper, we introduce an econometric model which enables us to test and estimate the different types of spatial heterogeneity using a generalised ordered logit model, whose threshold parameters depend on regional fixed effects (following Maddala, 1983; Terza, 1985). Using Geographic Information Systems (GIS), in addition to regional dummies, we include a large set of location-specific factors, linked to the respondent's dwelling area (as in Brereton et al., 2007), to control for spatial differences in location-specific amenities that affect true latent well-being in an attempt to mitigate the omitted variable bias and separate the effect due to the reference scale bias.

Furthermore, in order to avoid model misspecification, we take advantage of the flexibility of the generalised ordered logit model by letting income effects vary across the outcome distribution as in Boes and Winkelmann (2004a, 2006). Traditional ordered response models typically constrain all the coefficients to be constant across different levels of SWB (some authors refer to this as parallel regression or parallel line assumption, see Long, 1997; Williams, 2006). However, it has been shown that income may affect happiness in heterogeneous ways at different levels of SWB (i.e. income may exhibit slope heterogeneity) (see, e.g., Boes and Winkelmann, 2006; Clark et al., 2005). In addition, income may affect the reference scale of each respondent, with people being more likely to report a low or high SWB, for any given level of true individual well-being, according to their income. Income-related reporting heterogeneity exists for self-

[3] See Jurges (2007) for an example on how differences in self-assessed health can depend on the country of residence.

assessed health as an indicator of clinical health (see, e.g., Etilé and Milcent, 2006; Hernandez-Quevedo et al., 2005; Humphries and van Doorslaer, 2000) although the direction of the bias seems to be country-dependent. These two effects, on true well-being and on the reporting style, cannot be separately identified. Nevertheless, allowing for slope heterogeneity in income provides interesting information about income-happiness relationships.

We intentionally take a small country, the Republic of Ireland, to test for the presence of spatial heterogeneity. If heterogeneity is found to be significant in Ireland, it is even more likely to be present in larger countries and, in particular, in large cross-country comparisons. The analysis is done using micro-data and objective (and not perceived) environmental and social conditions, in an attempt to take care of endogeneity. Ireland is a small country positioned at the periphery of the European Union. It extends over 70,280 Km^2 with a total population of about 4 million, of which only 10% declared to be non-Irish, and 88% declared to be catholic in the 2002 Census (CSO, 2003). The economic boom of the recent years appears to have benefited all the regions when looking at conventional economic indicators (Walsh, 2006). These few statistics alone would show a homogenous country from social and demographic point of views. However, data from the 2002 Irish Census (CSO, 2003) show that the great majority of Irish people (almost 79.6% in 1996, and 78% in 2001) live in the same local authority of their birth suggesting a deep attachment to the local community in some areas. Does the region of birth matter for cross-comparability in SWB? We argue that not only the local environment and cultural heritage might be an important element in SWB, but that the location of residence can influence the frame of reference used by respondents. Hence cross-comparability could be limited even in small countries if regional differences and reference scale bias are not taken into account.

The results suggest that location has an effect on the reference scale used by the respondents when collapsing their well-being into the ordinal scale provided in the questionnaires, with people living in the West of Ireland having a higher reference point than, for instance, people living in the Dublin region. Our interpretation of this is that living in Dublin, the only metropolitan area of the country, shapes people's expectations upwards compared to the rest of the country. We conclude that spatial heterogeneity and reference scale bias should be taken into account in happiness studies, especially when comparing and ranking well-being across countries.

Finally, we find interesting patterns regarding income and environment effects on happiness when they are allowed to vary across outcome categories. The probability of reporting the bottom categories of SWB decreases with income, while the probability of scoring higher categories of SWB increases with income. However, income does not affect the probability of reporting the highest category of SWB. On the other hand, better environmental conditions (warmer temperatures and cleaner rivers) and social capital proxies (voter turnout and percentage of Irish speaking people) increase the probability of scoring the highest category of life satisfaction.

The paper is structured as follows. Section 2 explains the notion of spatial heterogeneity and region-driven reporting bias used in this paper and how it can be accounted for using a generalised ordered logit model. Section 3 presents the data. The results and hypothesis tests are presented in Section 4. The final section concludes.

2. Econometrics models and spatial heterogeneity

Space may affect reported SWB through two channels. First, people in different regions may enjoy different levels of local public goods, which may have an impact on "true" well-being. Second, the place of residence (and/or place of birth) may affect the frame of reference of each respondent and consequently introduce reporting bias in the SWB scores. The upper part of Figure 1 illustrates the process.

Figure 1 about here

The positive and significant effect of environmental attributes on quality of life has already being tested by some scholars using hedonic pricing models (with seminal contributions by Blomquist et al., 1988; Roback, 1982; Rosen, 1974, 1979) and more recently using SWB regressions (Brereton et al., 2007; Rehdanz and Maddison, 2005; van Praag and Baarsma, 2005; Welsch, 2002, 2006).

Scale of reference or reporting style bias usually refers to the phenomena that questions on well-being are answered relative to a certain reference group or situation, unobservable to the researcher, with consequent problems for comparability of SWB measures across groups of individuals. We argue that location may play a role in shaping the frame of reference of respondents. Tradition or rural and urban landscapes and places may shape people's expectations. For example, it is usually found that small low-income countries such as Bhutan score very high in happiness indices, while countries such as Japan fall well behind in those rankings (see for example The Happy Planet Index by Marks et al., 2006). Another famous and often-reported example in health economics is that self-reported health is much lower in the United States than in the Indian State of Kerala, where the mortality rate is larger than in the latter (Murray and Chen, 1992; 2002; Sen, 1995). Despite these paradoxes, the possibility of reference-scale bias in large samples used to analyse well-being across countries or regions has not been addressed by the literature so far. [4]

While physical environmental attributes are observable to the researcher, the frame of reference is not. From an empirical point of view, the situation is complicated by the fact that a comprehensive set of significant environmental variables is not readily available at a convenient spatial disaggregated level. This implies that the model may suffer from omitted variables bias. Therefore, in practice, part of the spatial heterogeneity determined by environment is unobserved if data on local public goods are not available. This situation is described by the bottom part of Figure 1. The relevant consequence of all this is that omitted environmental variables bias and reference scale bias cannot be identified separately. Panel and cross-section data on well-being have been analysed by OLS or by ordered response models (ordered probit/logit) where typically unobservable spatial heterogeneity is controlled for using region or country-dummies. However, these region or country dummies capture both reporting and omitted environment effects. In principle if all the significant environmental attributes were available to the researcher, then the dummy variables would capture only the reference scale bias. Our empirical strategy is to include in our model a large set of environmental factors (including environmental,

[4] Reference scale bias has received more attention in judging self-reported health as a reliable measure of health production within the realm of health economics (see, e.g., Gibbons, 1999; Groot, 2000; Jürges, 2007; Lindeboom and van Doorslaer, 2004; Sprangers and Schwartz, 1999; van Doorslaer and Gerdtham, 2003).

climate and social amenities), linked to each respondent's dwelling area using GIS techniques, in order to limit omitted variable bias. [5]

In ordered response models, true well-being is a latent, unobservable continuous variable that depends on location fixed effects and environmental amenities linked to the SWB scores by unknown parameters (thresholds or cut-off points) that discretise the latent variable in a number of intervals. Formally, J ordered happiness categories are the discretized version of an underlying continuous (latent) variable $v_{i,k}$ which corresponds in our case with "true individual's well-being":

$$v_{i,k} = \alpha + \mathbf{x}'_{i,k}\boldsymbol{\beta} + \delta_k + \varepsilon_{i,k}, \qquad \text{where } \varepsilon_{i,k} \sim (\eta, \sigma^2), \qquad i = 1, \ldots, N \text{ and } k = 1, \ldots, K-1. \quad (1)$$

$v_{i,k}$ is the true utility function for the *i-th* individual in location k that determines the SWB reported, $\mathbf{x}_{\mathrm{i,k}}$ is a vector of individual or location-specific variables. Let's suppose that the sample is divided in K locations, then δ_k are $K-1$ region dummy variables or fixed effects typically used to account for unexplained differences in SWB across locations. The unobserved true utility $v_{\mathrm{i,k}}$ is connected to the ordinal observed variable SWB through a series of unknown threshold parameters μ_{j} (or cut points) such that:

$$SWB_{i,k} = j \quad \text{if and only if} \quad \mu_{j-1} \leq v_{i,k} < \mu_j \ ,$$
$$\text{for } j = 1, \ldots, J \quad i = 1, \ldots, N \quad \text{and} \quad k = 1, \ldots, K. \qquad (2)$$

where $-\infty<\mu_0, \ldots, \mu_J < +\infty$. The $J-1$ thresholds that fully partition $v_{i,k}$, are unknown parameters to be estimated together with $\boldsymbol{\beta}$.

An econometric model relating the covariates to SWB can be constructed from (1) if a distributional function F for ε_i is specified such that the model can be estimated with standard likelihood methods. Hence:

$$\Pr(SWB_{i,k} \leq j | \mathbf{x}_{i,k}, \delta_k) = \mathrm{F}(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k)$$
$$\text{for } j = 1, \ldots, J-1 \quad \text{and} \quad k = 1, \ldots, K-1 \qquad (3)$$

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[5] As it will be specified later, the assumption required for the model to work is not that the omitted variables should be zero but that effect of the omitted variables should be the same across locations.

Without loss of generality, we assume $\alpha = 0$ because the intercept and the cut-off points cannot be identified simultaneously. The model will be unidentified unless an assumption is made about the variance of errors. When the logistic distribution is chosen (as in our case), it is usually assumed that $\text{var}(\varepsilon_{i,k})=\pi^2/3$ because this leads to a simple form of the model (Long, 1997) and the models are called ordered logit (Ologit, henceforth). From (3) the probability of an observed outcome for a given value of the covariates is the area between the two corresponding cut-offs points under the logistic distribution:

$$\begin{aligned}\Pr(SWB_{i,k} = j|\mathbf{x}_{i,k}, \delta_k) &= F(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k) - F(\mu_{j-1} - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k) = \\ &= \exp(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k)/\ 1 +(\exp(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k))\end{aligned}$$

$$\text{for } j = 1,\ldots, J-1 \quad \text{and} \quad k = 1, \ldots, K-1. \tag{4}$$

In the model given by (1)-(4), the contribution of the m^{th} covariate change (say, x_m) on the distribution of SWB responses is given by the marginal effects and depends on the other independent variables:

$$\begin{aligned}\partial\Pr(SWB_{i,k} = j|\ \mathbf{x}_{i,k}, \delta_k)/\partial x_m &= \partial F(\mu_j - \mathbf{x}'_m\boldsymbol{\beta} - \delta_k)/\partial x_m - \partial F(\mu_{j-1} - \mathbf{x}'_m\boldsymbol{\beta} - \delta_k)/\partial x_m \\ &= \beta_m[(f(\mu_{j-1} - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k) - f(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k)],\end{aligned} \tag{5}$$

where $f(\cdot) = \mathrm{d}F(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k)/\mathrm{d}(\mu_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} - \delta_k)$, $j = 1, \ldots, J$ and $k = 1,\ldots, K$.

In the case of location fixed effects, we refer more correctly to discrete changes. Discrete changes measure the effect on the probability of observing a particular outcome when changing the region of residence and they are given by:

$$\Delta\Pr(SWB_{i,k} = j|\ \mathbf{x}_{i,k}, \delta_k)/\Delta\delta_k = \Pr(SWB_{i,k} = j|\ \mathbf{x}_{i,k}, \delta_k = 1) - \Pr(SWB_{i,k} = j|\ \mathbf{x}_{i,k}, \delta_k = 0) \tag{6}$$

Equation (6) shows the restriction implied by standard ordinal models, which is common to OLS as well. The effect of each region is constant across SWB levels.

However, reference scale bias associated with location can be of two forms. First, the region of residence may affect the reporting style in the same way for all the SWB levels (i.e., when living in region *A* has an effect on the way in which people transform low levels of well-being into category "1" and high levels of well-being into "4" by a constant). In this case OLS models or standard ordered models would suffice. Second, what if the reference scales are different for each region? In this case, this "linear effect" can be easily relaxed in OLS by transforming the dependent variable (for example by taking its logarithm), but the only way of extending this concept to latent variables in ordered response models is by having different linear predictions at each threshold. This can be achieved by generalising the standard ordered logit/probit analysis, by modelling the thresholds parameters as a function of region or country-dummies. [6] In particular, the generalization proposed in our paper is derived from Maddala (1983), Terza (1985) and Williams (2006).

The model is particularly suitable for cross-section data where issues related to inter comparability are more different to control for. As for longitudinal data, if reference scale bias is time-invariant, then it can be controlled for by including specific individual fixed effects. [7]

Formally, in order to allow all the parameters of interest to vary across the $J - 1$ outcome categories, we let the cut-off points be linear functions of the covariates:

$$\mu_j = \kappa_j + \mathbf{x}'_{i,k}\boldsymbol{\lambda}_j + \eta_j\delta_k \quad \text{for } i = 1, \ldots, N, \quad k = 1, \ldots K - 1, \text{ and } \quad j = 1, \ldots, J - 1. \qquad (7)$$

In equation (7), η_j and λ_j are response specific parameters. Substituting (7) into (3) yields the cumulative probabilities in the Gologit.

$$\Pr(SWB_{i,k} \leq j|\mathbf{x}_{i,k}, \delta_k) = F(\kappa_j + \mathbf{x}'_{i,k}\boldsymbol{\lambda}_j - \mathbf{x}'_{i,k}\boldsymbol{\beta} + \eta_j\delta_k - \delta_k) = F(\kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k}),$$
$$j = 1, 2, \ldots, J - 1 \quad \text{and} \quad k = 1, 2, \ldots, K - 1. \qquad (8)$$

[6] For a brief overview and graphical representation of the parallel regression assumption see Appendix I.
[7] However, there are not aprioristic reasons to assume time-constancy of reference points. Therefore, even if the model we propose applied to a cross-section, as in our case, it can be applied on longitudinal data including time dummies in the threshold equation 7 (see for instance Boes and Winkelmann, 2006).

where $\boldsymbol{\zeta}_j = \boldsymbol{\beta} - \boldsymbol{\lambda}_j$ and $\delta_{j,k} = (1 - \eta_j)\delta_k$.[8] The probability of obtaining a particular outcome j is given by integrating over the density function $f(\cdot)$ with integration limits $\kappa_{j-1} - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_{j-1} - \delta_{j-1,k}$ and $\kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k}$. Specifying the distribution function F as a logistic, the model can be written as:

$$\Pr(SWB_{i,k} \leq j | \mathbf{x}_{i,k}, \delta_k) = F(\kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k}) =$$
$$= \exp(\kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k}) / 1 + \exp(\kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k})$$
$$j = 1,\ldots, J-1 \quad \text{and} \quad k = 1,\ldots, K-1 \tag{9}$$

Note, that the model in (9) is a fully-unconstrained Gologit (Fu, 1998), because it relaxes the parallel regression assumption for all the coefficients vectors. As our main interest in this paper lies in capturing flexibly spatial heterogeneity it is possible to conceive a more parsimonious *partial* Gologit model where only region effects are allowed to vary across J categories. Furthermore, since it has been shown that income may affect happiness in heterogeneous ways at different level of SWB (i.e., income may exhibit slope heterogeneity; see, e.g., Clark et al., 2005) in order to avoid model misspecification, we take advantage of the flexibility of the generalised ordered logit model by allowing income effects to vary across the outcome distribution as in Boes and Winkelmann (Boes and Winkelmann, 2004b, 2006). In addition, income may affect the reference scale of each respondent, with people being more likely to report a low or high SWB, for any given level of true individual well-being, according to their income. Income-related reporting heterogeneity has been documented for self-assessed health as an indicator of clinical health (Etilé and Milcent, 2006; Hernandez-Quevedo et al., 2005; Humphries and van Doorslaer, 2000) although the direction of the bias seems to be country-dependent.

The *partial* Gologit model[9] can be derived from (9) and can be written as follows:[10]

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[8] In order to obtain a well-defined probability function, the condition $\kappa_{j-1} - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_{j-1} - \delta_{j-1,k} < \kappa_j - \mathbf{x}'_{i,k}\boldsymbol{\zeta}_j - \delta_{j,k}$ has to be ensured (Terza, 1985; Winkelmann and Boes, 2006).

[9] When not otherwise specified, in the rest of the paper, the term Gologit will refer to the *partial* Gologit in (10) instead of the fully unconstrained Gologit in (9).

[10] The partial Gologit model was estimated using the Stata module `gologit2` written by Richard Williams (Williams, 2006).

$$\Pr(SWB_{i,k} \leq j | \mathbf{z}_{i,k}, y_i, \delta_k) = F(\kappa_j - \mathbf{z}_i \boldsymbol{\psi} - y_{i,} \boldsymbol{\omega}_j - \delta_{j,k}) =$$
$$= \exp(\kappa_j - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_{i,} \boldsymbol{\omega}_j - \delta_{j,k}) / 1 + \exp(\kappa_j - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_{i,} \boldsymbol{\omega}_j - \delta_{j,k})$$
$$\text{for } j = 1,\ldots, J-1 \quad \text{and} \quad k = 1,\ldots, K-1. \tag{10}$$

where there are three sets of coefficient estimates: $\boldsymbol{\psi}$, $\boldsymbol{\omega}_j$ and $\delta_{j,k}$. The $\boldsymbol{\psi}$ is a vector of parameter estimates that do not vary across outcome categories; the $\boldsymbol{\omega}_j$ are the $J-1$ parameters on income (y_i) for which the parallel regression assumption is relaxed; the $\delta_{j,k}$ are $K-1$ region effects that are allowed to vary across $J-1$ categories. The number of parameters to be estimated is then $J-1$ coefficients on income plus $J-1$ times $K-1$ region effects, plus the number of the $\boldsymbol{\psi}$ invariant parameters. Therefore the generalization comes with a reduction of degrees of freedom.

Furthermore, the Gologit model provides more flexible marginal effects or discrete changes. For example the marginal effects of income are given by the following:

$$\partial \Pr(SWB_{i,j} = j | \mathbf{z}_{i,k}, y_i, \delta_k) / \partial y_i =$$
$$= \partial F(\kappa_j - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_i \boldsymbol{\omega}_j - \delta_{j,k}) / \partial y_i - \partial F(\kappa_{j-1} - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_i \boldsymbol{\omega}_{j-1} - \delta_{j,k}) / \partial y_i =$$
$$= \omega_j [(f(\kappa_{j-1} - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_i \boldsymbol{\omega}_{j-1} - \delta_{j,k})] - \omega_{j-1} [f(\kappa_j - \mathbf{z}_{i,k} \boldsymbol{\psi} - y_i \boldsymbol{\omega}_j - \delta_{j,k})], \tag{11}$$

and for the regional effects, the discrete changes can be derived in this way:

$$\Delta \Pr(SWB_{i,k} = j | \mathbf{z}_{i,k}, y_i, \delta_k) / \Delta \delta_k =$$
$$= \Pr(SWB_{i,k} = j | \mathbf{z}_{i,k}, y_i, \delta_k = 1) - \Pr(SWB_{i,k} = j | \mathbf{z}_{i,k}, y_i, \delta_k = 0). \tag{12}$$

The standard Ologit in (4) is nested in the Gologit in (10) where the following constraints apply: $\boldsymbol{\omega}_1 = \boldsymbol{\omega}_2 = \ldots = \boldsymbol{\omega}_{J-1}$ (i.e, the parameters on income are constrained to be equal at each parallel line) and $\delta_{1,k} = \delta_{2,k} = \ldots = \delta_{J-1,k}$ (i.e, the region effects do not vary across SWB levels). It follows that a test of the parallel regression assumption can be performed contrasting Ologit versus Gologit with a Wald test.[11]

[11] It is possible for SWB responses to be correlated within K locations. If this happens, it has been shown that the conventional standard errors are biased (Moulton, 1990; Williams, 2000). One way to solve for this and to get unbiased standard errors is to compute standard errors adjusted for intraclass correlation (Rogers, 1993), which is the strategy adopted in this paper. However, in practical terms this means that conventional

$$H_0\text{: } \boldsymbol{\omega}_1 = \boldsymbol{\omega}_2 = \ldots = \boldsymbol{\omega}_{J-1} \text{ and } \delta_{1,k} = \delta_{2,k} = \ldots = \delta_{J-1,k} \text{ for every } k\text{-}th \text{ region effect.} \qquad (13)$$

If the null is rejected then the use of the Ologit parallel model provides biased estimates, i.e., the parallel regression assumption does not hold. This implies also that the Gologit model performs better than the Ologit. The test in (11) is also a test for the joint presence of income and region heterogeneous effects at each threshold.

A second series of tests that the Gologit specification let us emphasise more explicitly the hypothesis of flexible spatial heterogeneity in SWB adopted in this paper:

$$H_0\text{: } \delta_{1,1} = \delta_{1,2} = \ldots = \delta_{1,K-1}$$
$$H_0\text{: } \delta_{2,1} = \delta_{2,2} = \ldots = \delta_{2,K-1}$$
$$\ldots$$
$$H_0\text{: } \delta_{J-1,1} = \delta_{J-1,2} = \ldots = \delta_{J-1,K-1} \qquad (14)$$

Tests in (14) checks for the existence of outcome-specific region effects, i.e., we are asking whether living in a location instead of any other matters at each threshold.

Finally, we will test for heterogeneous income effects as follows:

$$H_0\text{: } \boldsymbol{\omega}_1 = \boldsymbol{\omega}_2 = \ldots = \boldsymbol{\omega}_{J-1} \qquad (15)$$

(we refer to it as a test for income slope heterogeneity)

We expect region effects at each threshold to be statistically different even after controlling for a large set of covariates and local amenities.[12] If the null in (13) is rejected then we confirm that region of residence has a significant impact on SWB, that this effect varies across outcome categories, and that a (notable) part of this effect is due to

hypothesis tests based on likelihood ratio, that are usually preferred to compare nested models cannot be used (see Long and Freese, 2005). This is the reason why we use Wald tests on the joint equality of the coefficients.

[12] The covariates are described in the next section. They include demographic and individual characteristics; other standard factors usually considered to assess the quality of life in regional and urban areas in hedonic studies (such as employment rate, crime rate, congestion, climate, quality of the environment); and level of social capital.

reference scale bias. As regards to income, the null in (15), we expect income to be significantly different at each threshold as in Boes and Winkelmann (2004a, 2006).

3. Data

Micro-data on individual SWB and on socio-demographic and socio-economic characteristics come from the first Urban Institute Ireland National Survey on Quality of Life (Urban Institute Ireland, 2001) where a representative sample of 1,500 men and women, aged 18 and over and living in Ireland were interviewed face-to-face on quality of life issues and life satisfaction. [13]

The SWB indicator is an ordinal variable based on the answer to the following question: "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 an ordinal scale from one ('as bad as can be') to seven ('as good as can be'). Due to the low number of observations in the first four categories (from 'as bad as can be' to 'alright'), they were aggregated and recoded as one for econometric purposes.

The survey's dataset contains several variables typically used in the happiness literature as controls (see Frey and Stutzer, 2002b; Oswald, 1997; van Praag and Ferrer-i-Carbonell, 2004): age, gender, marital status (married and cohabiting), family size, educational attainment (primary school, lower secondary and upper secondary school) and employment status (based on ILO classification as self-employed, part-time, full-time, student, house keeping, unemployed).

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[13] Due to missing observations the final sample consists of approximately (depending on the model specification) 1,358 observations. The effective response rate is 66.6 percent. The margin of error using the entire sample is ± 2.5 percent at a 95 percent confidence level. The 2000 Register of Electors was used as the sampling frame. The register is inclusive of all individuals nominated on Electoral Registration forms returned in July 2000. The register is compiled on a Local Authority basis of which there are 34 in Ireland. The sampling procedure adopted was a two stage proportionate random sampling procedure using probability proportionate to size (PPS). The rationale governing this choice of design was to ensure coverage of all 34 Irish Counties with proportionate representation of all county areas. In selecting potential respondents from each, a computerised random numbers procedure was again used to ensure that each elector listed had an equal chance of being selected. All interviews were conducted during the period 12 March 2001 to 25 May 2001. To test for non-response bias, four key variables from the sample (age, sex, marital status and economic activity) were compared with corresponding Irish census estimates. Given the broad representativeness of the sample, no corrective weighting procedures were applied to the data (see Urban Institute Ireland, 2001).

A measure of gross household income completes the micro-level data used in the analysis. Because missing values represented 23.7% of those interviewed, a predicted log of reported gross income was used in the regression as in Luttmer (2005).[14] The value of predicted logarithmic income used in the analysis is the linear prediction of an OLS regression of continuous income on the following set of covariates: age, age-squared, gender (male), marital status, educational attainment, a dummy variable for Dublin, occupational status (full-time or part-time job, occupation in Government or public agencies, disabled, retired, student and keeping the house) and finally a measure of wealth (being a house-owner).

The Republic of Ireland is divided into regional authorities (RAs), local authorities (LAs) and electoral divisions (EDs) for administrative purposes. Figure 2 shows the list of RAs and Table 1 illustrates how these are then subdivided into LAs. Spatial heterogeneity was analysed at regional level using eight Irish Macro-region effects: Dublin, Mid-East, South-East, South-West, Mid-West, West, Border and Midland. LAs and EDs were used to spatially reference environmental, climate and socio-economic factors using Geographic Information System techniques.[15] LAs generally equate to one body per county and one for the four major urban areas of Galway City, Limerick City, Cork City and Waterford City. ED is the smallest enumeration area used by the Irish Central Statistics Office in the collection of Census data. There are over 3,440 EDs in Ireland. These areas are relatively small, particularly in the city regions and those represented in our sample range in size from 18 hectares (in cities) to 6,189 hectares (open countryside)[16] with total populations ranging from 47 individuals to 8,595.[17] The Urban Institute Ireland National Survey on Quality of Life includes information on the ED where the respondent lives. Therefore the available micro-data can be merged with

[14] The original income variable was divided in 10 categories, so mid-points were used with the last category being dropped (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.

[15] The Geographic Information System (GIS) is a computing tool that enables the analysis and visual representation of spatially referenced data.

[16] Mean = 1,767, standard deviation = 1,538.

[17] Mean = 2,040, standard deviation = 2,073.

detailed geographic information at ED level (or, in a small number of cases their LA when environmental data were not available at ED level).[18]

Figure 2 about here

As in (Brereton et al., 2007), the availability of spatial data and their visualisation via GIS considerably expands the number of variables that can be included in the SWB regression. Typically, previous studies in the literature either control for one attribute only (for instance, perception of noise in van Praag and Baarsma, 2005) or they use a macro-econometric SWB function where each country is a cross-sectional unit (see Welsch, 2006). In our specific case, linking respondents to their objective living circumstances at a very high level of disaggregation - the ED where the individual's dwelling is situated – allows us to reduce the omitted variable bias component of the unobservable spatial heterogeneity, therefore making possible to asses the importance of reference scale bias.[19]

In the literature it is recognized that, at local level, "the linkage between environment and happiness is even more articulate than it is with respect to national data" (Welsch, 2006, p. 11).

Because of the few references available in the SWB literature, the specific local amenities considered in this paper were mainly drawn from other economics fields, such as urban, regional and environmental economics, where the study of the effects of location-specific factors on individual well-being has more than three decades of tradition using quality of life indices from hedonic pricing studies (Blomquist et al., 1988 for early contributions ; and Gyourko et al., 1999, for a critical review; Roback, 1982; see Rosen, 1974; Rosen, 1979).

Our study includes socio-economic, demographic and environmental factors. We used violent crime rate at LA level (measured as rate of crime incidents per thousand of

[18] See (Brereton et al., 2007) for a detailed account of the methodology and the first implementation of GIS techniques in the economics of happiness literature.
[19] The reason why we cannot use LAs or ED fixed effects instead of regional fixed effects is to avoid the incidental parameter problem. As shown in Table 1, the number of observations by regions ranges from 107 (Mid-east) to 395 (in Dublin), while looking at LA level the number of observations would have been too small, ranging from 2 in Leitrim to 171 in Dublin City.

population; Garda Síochána, 2001) unemployment rate at ED level[20] (CSO, 2003); and population density (measured as total population divided by the total area in Km2) as in Roback (1982) and Blomquist et al. (1988).Additionally, we controlled for population change over the period 1996-2001, when Ireland experienced a dramatic migration turnaround after 150 years of population loss due to emigration (CSO, 1997, 2003).[21] Additionally, average commuting time in the local authority area in 2002 (CSO, 2003) was included to capture congestion problems.

Local environmental amenities consist of climate, pollution, waste facilities and proximity to coast variables. The effect of climate on well-being is well-documented in the hedonic models literature (Blomquist et al., 1988) and in the happiness literature as well (see Brereton et al., 2007; Frijters and Van Praag, 1998; Rehdanz and Maddison, 2005). Different climate variables were considered for this study (including wind speed, mean annual duration of sunshine, mean annual precipitation). Because of strong correlation between the climate variables we decided to include only the temperature variables in the final model. The temperature variables that best describe and predict the behaviour of the other climate variables are the average minimum temperature registered in January and the average maximum temperature registered in July (measured at LA level by Collins and Cummins, 1996).

Local air pollution is expressed in terms of annual mean ambient mass concentration of PM_{10} in micrograms per cubic meter. Ireland is divided into four air quality zones in order to implement the European Union Directive on Air Quality Assessment and Management (see for instance CEC, 1996; EPA, 2002). Air quality is considered homogeneous within each of the 4 areas. They are Dublin city and environs (zone A), Cork city and environs (zone B), 16 urban areas with population greater than 15,000 (zone C) and the rural areas in the rest of the Country (zone D). In 2001, zone B, C and D were monitored on a daily basis using two fixed stations in B and D and a mobile unit in zone C placed in locations representative of the entire areas. Zone A was monitored with seven fixed monitoring stations positioned in different areas in the Dublin RA. Pollution

[20] If not otherwise specified, variables are disaggregated at ED level.
[21] For example, from Census data (CSO, 1997; and 2003), the total number of those residing outside of the Republic of Ireland during the previous year passed from 37,000 in 1991 to 76,000 in 2002.

levels recorded in the monitoring stations were assigned to our observations on the basis of the proximity of the respondent's ED to the monitoring stations. In the case of the respondent's ED being near to more than one monitoring station, a weighted average of the different values was attributed as local mass concentration of PM_{10}. Water pollution is measured by a dummy variable capturing proximity to a 'seriously polluted river' as defined by EPA (2005). [22]

GIS data enable us to match all the EDs that contain at least one landfill or are on the coast. There is evidence in the literature on quality of life that smell (approximated by proximity to a landfill) is a disamenity that negatively affects well-being (see Blomquist et al., 1988; and Brereton et al., 2007), while living near a coast usually has a positive effect.

We also considered other location-specific factors to try to capture cultural differences of some parts of Ireland where Irish tradition and the social environment are considered to be particularly important. In Ireland there are two official languages, English and Irish Gaelic. Irish is diffuse in some areas known as Gaeltacht (Irish term for Irish speaking). These areas are in the western counties of Donegal, Mayo, Galway, Kerry, and Cork (see Figure 2). There are smaller concentrations in the counties of Waterford in the south and Meath in the east. The *Department of Community, Rural & Gaeltacht Affairs* is a specific government agency responsible for overall Irish Government policy with respect to these areas. A further example of the importance of Irish tradition and communities is the existence of a national radio station and a television broadcast (Radió na Gaeltachta and TG4) in Ireland focussing on promoting the Irish language. We considered the following variables as proxies for the quality of the social environment (or social capital): the percentage of people speaking Irish in each local authority and voter turnout available at ED area (CSO, 2003).[23]

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[22] PM10 and polluted rivers data were provided by EPA Ireland (www.epa.ie) in electronic format. 'Seriously polluted river' captures the presence of biologically polluted water bodies within 2 km from each ED.

[23] Some models were run including other proxies of social capital: a dummy variable expressing self assessed personal commitment to the community (taking value of 1 if the person is 'very committed' or 'committed' and 0 otherwise) and respondent's assessment of the sense of the community in the areas (taking value of 1 if community sense is considered 'excellent' or 'good' and 0 otherwise). The results did not change, so we eliminated them from the analysis in order to avoid endogeneity.

4. Results and discussion

Table 1 shows the variation of the 7 category-scale SWB by RA and LA. The average SWB in Ireland is relatively high, 5.47, between ‘good’ and ‘very good’ on the SWB scale used in the survey, with a standard deviation of 0.99. Only about 2.20% report a low SWB score (‘as bad as can be’, ‘very bad’, ‘bad’), while about 84% report a good SWB score (‘good’, ‘very good, ‘as good as can be’). Within this group, those stating they are ‘as good as can be’ (category 7) are 14.18% of the total. A simple visual inspection of Figure 3 confirms that differences in SWB exist across locations no matter if 7 or 4 SWB categories are considered. The same Figure shows that the first 3 outcome distributions are missing for some regions. Particularly different from that of Ireland as a whole, is the shape of the distribution of SWB among happiness categories in the West Region.

Key descriptive statistics of the micro and spatial data across regions is presented in Tables 2 and 3. In our sample, some differences across locations can be found in the age and education structure (with the oldest of the sample living in the West and the youngest in the Mid-East) and employment condition (with a notable proportion of self-employed in the Midland and South East Regions). Particularly interesting are the distributions of predicted log-income and the unemployment rate (standard measures of well-being) that appear to show quite a homogeneous country (see also Walsh, 2006).

The level of violent crime is notably different across regions with Dublin reporting the highest rates, five times greater than in the West. There seems to be some variation in the winter temperature with the coldest regions being Mid-East and Midland and the warmest being Dublin. The Border and the West experience the mildest temperatures in July, while the two South regions have warmer temperatures. Air pollution (in terms of PM_{10} emissions) is high in the Dublin Region as expected. Western regions have the highest rate of both people speaking Irish and voter turnout.

Table 1, 2, 3 about here

As discussed in Section 3, Wald-tests were run to check for the appropriateness of the parallel line assumption on income and region effects (see (13)). The equality of the coefficients across outcome categories can be rejected at 1% significance level. This implies also that the effects of income and location are heterogeneous across SWB levels. Furthermore, the specific null in (13) and (14) were rejected at 1% significance level as well. The conclusion is that the income and region effects affect SWB in a heterogeneous way. Standard ordered models would not be able to capture this effect. Moreover, as suggested in Section 2, part of the income and region effects comes from effects on "true" well-being, while another part may come from effects on the reference scale of each respondent. The following analysis will show that it is likely that at least a good portion of the region effects might be driven by differences in the scale of reference. This might mean that people living in, say, Dublin region apply a different scale than people living in West region when translating their "true" well-being into the given categories in the questionnaire and that their reference scale varies across outcome categories.

Following the results of the tests, estimations for the traditional Ologit model are not discussed any further. Moreover, as the coefficients from ordered response models provide only an indication of the direction of an effect but not of its magnitude (as discussed in Section 2), we concentrate on the marginal effects for the Gologit model. [24]

Table 4 reports the marginal effects of logarithmic income and, as we are mainly interested in spatial heterogeneity, regions and spatial (macro) factors on self-reported SWB. Looking at the results for income, the marginal effects suggest that as income increases, the probability of reporting low level of SWB decreases. For example, an increase of income by 1 percent decrease the probability of reporting $J = 1$, $J = 2$ by 0.2% and 0.14%, respectively, (though this last effect is not statistically significant), while increases the chances to report $J = 3$ by a significant 0.34%. The marginal effect at the last threshold is close to zero and is not statistically significant. This result conforms with that of Boes and Winkelmann (Boes and Winkelmann, 2004a, 2006) and suggests that income buys happiness up to a certain level, after which further increases in income do not have significant impact on happiness.

The δ regional heterogeneous effects in Table 4 correspond to seven Irish RAs, where the reference region is Midland (i.e., all the results are reported relatively to living in Midland, however the results are not affected by the change of the reference region).

[24] A table showing all coefficient estimates from Ologit and Gologit can be found in Appendix II.

Interestingly, Dublin region has a negative effect on the last threshold, meaning that the probability of reporting the highest level of SWB decreases by 0.08% when the respondent lives in Dublin. In other words, living in Dublin is negatively correlated with the probability of reporting 'very good' and 'as good as can be' (although for the former the discrete change is not statistically significant), and is positively correlated with reporting the lowest categories of SWB.

Dublin Region coincides with the metropolitan area of Dublin, Ireland's capital. Dublin is the only urban area in Ireland with a population in excess of 150,000 and with about 1 million inhabitants it comprises about 25 percent of a total population of about 4 million in 2001, historically showing a great capacity of attraction of people (CSO, 2003). However, concerns regarding the implications of the rapid economic growth in Ireland over the 90s for localized environmental quality and well-being have mostly centred in Dublin, which has experienced the most rapid growth – unparalleled in Europe (Clinch et al., 2002; Honohan and Walsh, 2002). On the other hand, by international standards, Dublin cannot be compared with other metropolitan areas in the world where environmental problems can affect the quality of life above and beyond the variables we include. The interesting point here is that even if we control for a series of environmental variables that are typically disamenities in urban studies (i.e., congestion, PM_{10} emissions, etc.), the Dublin region dummy still negatively affects SWB. Living in the Mid-East, the adjacent region, negatively affects the probability of reporting low happiness scores (i.e., by 0.04% the probability of $J = 1$– although not statistically significant – and by 0.14% the probability of $J = 2$) while positively affects the highest level of SWB (by although these effects are not statistically significant). Almost the same situation is reported for the people living in the Mid-West; whose probability of reporting 'as bad as can be' to 'alright' decreases by -0.07%. Living in the Border region decreases the probability of scoring the highest SWB by a significant 0.05% (while it increases the probability of belonging to lowest category, although the discrete changes are not statistically significant). The most remarkable result is the one associated with living in the West of Ireland. Even after controlling for location-specific amenities including social capital and the percentage of people speaking Irish language, living in the West of Ireland is strongly correlated with a decreased likelihood of being in the lower part of the SWB ladder and with an increase in the probability of reporting the highest level of SWB. The probability of reporting *J* = 1 and *J* = 2 decreases by 0.4 and 0.3%, respectively (with only the latter being statistically significant) if the individual lives in the West, while it increases the probability of stating 'as good as can be' by 0.5%.

Regarding the spatial amenities, the results are as expected with the exception of living near to a coast, which negatively affects high levels of SWB. An increase in the average minimum temperature in January leads to a decrease in the probability of belonging to the lowest happiness categories of 'as bad as can be/alright' and 'good' by 0.09 and 0.14, respectively, while increasing in the probability of stating 'very good' and 'as good as can be' by 0.17 and 0.06. The same pattern can be seen for all the environmental amenities. For example, an increase of air pollution (measured by PM_{10} emissions) decreases the likelihood of reporting the highest two categories of SWB by 0.4% and 1% respectively. This general pattern can be summarized as follows: increases in environmental quality decrease the probability of reporting a low level of SWB and increase the chances to report high level of SWB. This can be contrasted with the finding that income does not have a significant impact on the probability of reporting the highest level of SWB. This suggests that to achieve the highest level of SWB, factors other than income may play a big role. Our model suggests that environment is clearly one of those factors, even when taking into consideration differences in the reference scale of each region.

Table 4 about here

Spatial heterogeneity can be investigated a bit further. Are the differences in SWB between West and Dublin due to objective unobservable characteristics? We argue that the inclusion of a large set of location specific factors and the significance of the variables included, suggests that the difference might be in the reference scale. People in the West are more likely to 'report' high levels of SWB than people in Dublin, for any given level of true well-being. This argument cannot be tested with the data available to us, but an analysis of the thresholds reveals some interesting insights that support the idea of reference scale differences. The difference in the thresholds among regions is visually illustrated in Figure 4, where every region-specific threshold in (7) has been predicted and compared with a hypothetical threshold (at every level J =1, 2 and 3). These hypothetical thresholds are represented by the vertical lines and were computed as the predicted thresholds for an individual with average income and then normalized. Again, the results do not change if one changes the region of reference. The relative distance between a single region effect and each hypothetical threshold, does not depend on the arguably strong assumption of *zero* omitted variables, but that the omitted variables have to affect each region in the same way. The dots in Figure 4 correspond to the region-specific thresholds and the horizontal distance between the dot of a region and the vertical line can be interpreted as a rough estimate of the magnitude of the reference scale bias in each region. The regions are always in the same portion of the plane (always on the right, the 'optimistic', or on the left, 'the pessimistic', of the hypothetical threshold), while others (i.e., Mid-West) are very close to the average threshold. In particular, we estimate that respondents living in Dublin Region have reference scales that are 8-13% consistently lower that the average individual, which are the lowest among all the regions. Contrary, people living in the West Region have reference scales 1.30-1.75 times higher than the average individual. Residents in the Mid-East Region have 9-17% higher thresholds than the average individual. In absolute terms, the estimated reference scales are higher for the less-satisfied for all the regions. Our interpretation of this is that living in Dublin Region, the only metropolitan area of the country, shapes people's expectations upwards compared to the rest of the country.

Figure 4 about here

5. Conclusion

In this paper, we introduce an econometric model which enables us to test for spatial heterogeneity in subjective well-being using a generalised ordered logit model, whose thresholds parameters depend on regional fixed effects. Using Geographic Information Systems (GIS), we include a large set of location-specific factors, linked to the respondent's dwelling area (as in Brereton et al., 2007), to control for spatial differences in location-specific amenities in an attempt to mitigate the omitted variable bias and separate the effect due to the reference scale bias.

If the region affected the reporting style in the same way for all the SWB levels then standard ordered models would suffice. The generalized model we propose relaxes the parallel assumption and, in so doing, it allows each region to influence differently each response category. This means that the model permits the reference scale to be different for each threshold and for region.

In order to avoid model misspecification, we relax the parallel assumption on income as well. As previous research shown, income may exhibit slope heterogeneity. In addition, income may affect the reference scale of each respondent, with people being more likely to report a low or high SWB, for any given level of true individual well-being, according to their income.

The results suggest that spatial heterogeneity has a significant impact on the differences in the reference scale used by the respondents when collapsing their well-being in the ordinal scale provided in questionnaires. Environmental amenities have a positive effects on well-being, suggesting that environmental policies are unambiguously well-being enhancing. However, environment explains spatial heterogeneity of well-being up to a level. Differences in well-being across location arise from different frames of reference too. For instance, those living in the capital city Dublin on the East coast have reference points that are consistently 8-13% lower than that of an average individual, while people living in the Mid-West has a reporting bias 1.30-1.75 times higher. We conclude that spatial heterogeneity and reference scale bias should be taken into account in happiness studies, especially when SWB scores have been used to rank and compare countries with different languages and cultures.

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Table 1

Average SWB by Regional and Local Authority Areas in Ireland (2001)

Local Authority	Mean SWB	Std. Dev. SWB	Freq.	%
Dublin Region	**4.98**	**0.98**	**390**	**26.8%**
Dublin City	4.76	0.95	165	11.3%
Dublin South	4.68	1.16	80	5.5%
Dublin Fingal	5.63	0.60	64	4.4%
Dun Laoighaire	5.21	0.79	81	5.6%
Mid-East	**5.65**	**0.89**	**144**	**9.9%**
Kildare	5.16	0.78	64	4.4%
Meath	5.72	0.46	39	2.7%
Wicklow	6.37	0.86	41	2.8%
South-East	**5.73**	**0.99**	**154**	**10.6%**
Carlow	5.60	1.27	20	1.4%
Kilkenny	5.63	0.61	30	2.1%
South Tipperary	6.78	0.55	32	2.2%
Waterford City	5.71	1.38	7	0.5%
Waterford County	4.76	0.44	21	1.4%
Wexford	5.55	0.79	44	3.0%
South-West	**5.73**	**0.99**	**154**	**10.6%**
Cork City	5.43	1.04	51	3.5%
Cork County	5.53	1.05	115	7.9%
Kerry	5.74	0.56	53	3.6%
Mid-West	**5.58**	**0.66**	**146**	**10.0%**
Clare	5.36	0.57	47	3.2%
Limerick City	6.05	0.71	19	1.3%
Limerick County	5.73	0.57	51	3.5%
North Tipperary	5.38	0.73	29	2.0%
West	**6.34**	**0.92**	**139**	**9.6%**
Galway City	6.67	0.80	21	1.4%
Galway County	6.89	0.31	56	3.8%
Mayo	5.90	0.98	42	2.9%
Roscommon	5.33	0.80	21	1.4%
Border	**5.31**	**0.80**	**181**	**12.4%**
Cavan	5.21	0.78	24	1.6%
Donegal	5.25	0.84	52	3.6%
Leitrim	5.75	1.06	12	0.8%
Louth	5.51	0.68	39	2.7%
Sligo	5.13	0.76	31	2.1%
Monaghan	5.26	0.75	23	1.6%
Midland	**5.48**	**0.86**	**82**	**5.6%**
Laois	5.45	0.69	20	1.4%
Longford	5.27	0.47	11	0.8%
Offaly	5.84	0.94	25	1.7%
Westmeath	5.23	0.95	26	1.8%
Overall Ireland	**5.47**	**0.99**	**1456**	

Table 2

Descriptive statistics of micro-level variables

	Dublin	Mid-East	South East	South West	Mid-West	Border	Midland	West
Tot. observations	392	145	161	231	147	184	82	142
Gender								
Female	55%	56%	51%	54%	52%	47%	49%	48%
Male	45%	44%	49%	46%	48%	53%	51%	52%
Age								
N	391	145	160	229	146	184	81	141
Mean	43.4	39.4	43.3	43.1	40.6	46.5	42.7	50.3
Std. Deviation	16.7	15.7	16.5	17.8	15.5	18.4	18.1	16.1
Min	18	18	18	18	18	18	18	19
Max	87	82	84	88	86	89	90	87
Education level								
N	381	135	161	218	142	178	79	142
Primary	17%	10%	6%	10%	6%	30%	18%	13%
Lower Secondary	23%	31%	22%	14%	5%	15%	14%	28%
Upper Secondary	48%	40%	65%	57%	46%	37%	48%	46%
Non-Degree	4%	9%	4%	7%	20%	8%	6%	8%
Degree/ Post degree	9%	10%	4%	12%	23%	10%	14%	5%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Marital Status								
N	392	145	161	231	147	184	82	142
Married	52%	51%	50%	48%	57%	49%	57%	56%
Single	34%	36%	33%	41%	39%	37%	26%	33%
Cohabit	2%	4%	3%	3%	1%	2%	2%	1%
Separated/divorced	4%	3%	6%	2%	0%	2%	5%	4%
Widowed	8%	6%	7%	6%	3%	10%	10%	6%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Family size								
N	388	144	154	231	146	184	82	142
Mean	3.4	3.6	3.0	3.6	3.6	3.3	3.6	3.2
Std. Deviation	1.5	1.6	1.5	1.7	1.5	1.8	1.8	1.7
Min	1	1	1	1	1	1	1	1

Max	8	8	8	11	7	10	11	9
Employment status								
N	392	145	161	231	147	184	82	142
Self-employed	4%	5%	17%	5%	8%	14%	17%	14%
Full-time	41%	36%	34%	34%	44%	34%	26%	36%
Part-time	7%	10%	5%	8%	4%	10%	5%	11%
Student	3%	12%	3%	9%	9%	4%	11%	0%
Keep house	27%	27%	17%	20%	20%	13%	21%	8%
Others	18%	10%	24%	24%	15%	25%	21%	30%
Unemployed	4%	1%	3%	2%	2%	4%	5%	1%
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Log of predicted income								
N	388	144	159	225	142	180	80	140
Mean	9.9	10.0	9.9	9.9	10.1	9.8	9.9	9.9
Std. Deviation	0.3	0.3	0.3	0.3	0.5	0.4	0.4	0.4
Min	8.7	8.3	8.8	8.5	8.2	8.4	8.7	9.2
Max	10.5	10.5	10.5	10.5	10.5	10.5	10.5	10.5

Table 3
Spatial factors level variable (at ED or local authority level)

	Dublin	Mid-East	South East	South West	Mid-West	Border	Midland	West
Violent crime rate at local authority level (measured as rate of headline offences per thousand of population)								
N	389	145	161	229	147	184	82	142
Mean	65.55	18.42	20.73	15.65	18.23	13.87	17.33	13.00
Std. Deviation	46.63	1.93	11.78	5.43	3.19	3.01	1.86	2.44
Min	18.59	15.76	13.55	11.83	13.55	9.58	13.55	9.58
Max	120.06	21.97	120.06	24.21	21.48	18.59	23.29	15.26
Unemployment rate at ED level								
N	390	145	160	230	147	183	82	141
Mean	6.158	3.617	5.977	5.584	4.997	7.325	4.321	6.881
Std. Deviation	3.504	0.522	1.817	3.907	2.140	2.646	1.021	4.828
Min	2.680	2.720	1.520	2.040	2.490	1.330	2.110	2.050
Max	15.860	4.460	8.600	12.500	10.140	11.110	6.040	16.490
Population density at ED level								
N	390	145	158	229	147	183	82	140
Mean	40.56	0.80	2.79	0.14	18.95	0.55	0.41	5.46
Std. Deviation	27.39	1.00	10.00	0.13	27.30	0.93	0.30	10.47
Min	1.29	0.05	0.06	0.03	0.14	0.05	0.16	0.01
Max	149.96	2.74	45.93	0.42	104.39	5.40	1.01	38.59
Population change (96-02) at ED level								
N	390	145	158	230	147	184	82	118
Mean	3.38	13.61	10.12	14.34	29.85	4.09	21.63	4.30
Std. Deviation	15.34	9.39	12.33	19.36	43.71	7.23	44.84	7.88
Min	-12.10	3.30	-10.10	-13.30	-2.00	-5.10	-7.50	-25.40
Max	46.80	29.10	29.30	52.20	181.70	24.00	119.20	19.90
Average commuting time at local authority level								
N	390	145	160	230	147	183	82	142
Mean	30.9	34.3	24.6	20.5	25.3	24.1	27.7	22.3
Std. Deviation	4.5	8.1	4.3	3.0	7.1	6.7	10.2	5.9
Min	23.9	19.7	14.4	16.8	18.3	14.0	16.1	15.0
Max	39.3	44.4	38.3	27.0	43.5	36.2	45.6	29.0
January mean daily minimum temp (°C)								
N	390	145	160	230	147	183	82	142

Mean	2.6	1.6	2.3	2.8	2.2	2.3	1.6	2.3
Std. Deviation	0.4	0.4	0.6	0.6	0.2	0.7	0.2	0.5
Min	2.0	1.5	1.5	2.0	2.0	1.5	1.5	1.5
Max	3.0	2.5	3.0	4.0	2.5	3.5	2.0	3.5
July mean daily maximum temp (°C)								
N	390	145	160	230	115	183	82	142
Mean	19.5	19.6	19.8	19.5	19.1	18.2	19.6	18.3
Std. Deviation	0.4	0.4	0.2	0.6	0.3	0.7	0.3	0.5
Min	18.5	19.0	19.5	18.5	18.5	17.0	19.0	17.5
Max	20.0	20.0	20.0	20.0	19.5	19.0	20.0	19.0
Annual mean ambient mass concentration of PM_{10} (µg/m^3)								
N	392	145	161	231	147	184	82	142
Mean	24.0	19.0	19.2	21.0	19.8	19.0	19.1	19.7
Std. Deviation	5.3	0.0	0.9	3.2	1.9	0.0	0.6	1.7
Min	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0
Max	38.0	19.0	24.0	26.0	24.0	19.0	24.0	24.0
People living within 2 Km from a seriously polluted river (1/0)								
N (%)	46%	21%	0%	0%	0%	10%	0%	0%
Presence of a landfill in the respondent ED								
N(%)	27%	10%	11%	16%	10%	12%	6%	9%
Presence of a coast in the respondent ED								
N(%)	27%	10%	11%	16%	10%	12%	6%	9%
People speaking Irish language at local authority level								
N	390	145	160	230	147	183	82	141
Mean	38%	40%	42%	48%	49%	40%	43%	50%
Std. Deviation	3.2	2.1	3.7	1.8	3.2	3.1	1.8	2.4
Min	35%	38%	35%	45%	42%	36%	41%	46%
Max	42%	44%	48%	49%	51%	53%	49%	53%
Voter turnout at ED level								
N	390	145	160	230	147	183	82	141
Mean	54%	59%	64%	66%	61%	68%	69%	63%
Std. Deviation	8.9	5.5	5.3	7.0	7.4	5.7	6.1	6.7
Min	35%	48%	51%	55%	44%	57%	58%	56%
Max	69%	70%	72%	79%	70%	81%	82%	75%

Table 4
Marginal effects of selected variables after Gologit– dependent variable: SWB (j=1,…, 4)

	Gologit			
	J = 1	*J = 2*	*J = 3*	*J = 4*
Heterogeneous effects				
Predicted log-income	-0.207***	-0.136	0.335***	0.008
	(0.051)	(0.083)	(0.096)	(0.037)
δj,1[Dublin Region]	0.098	0.043	-0.091	-0.050**
	(0.079)	(0.084)	(0.126)	(0.034)
δj,2[Mid-East Region]	-0.030	-0.150*	0.009	0.172
	(0.047)	(0.084)	(0.123)	(0.107)
δj,3[South West Region]	0.092	0.016	-0.141	0.036
	(0.088)	(0.119)	(0.134)	(0.065)
δj,4[South East Region]	0.012	-0.062	-0.075	0.125
	(0.058)	(0.096)	(0.107)	(0.093)
δj,5[Mid West Region]	-0.054*	0.032	0.015	0.007
	(0.049)	(0.111)	(0.115)	(0.056)
δj,6[Border Region]	0.016	0.006	0.021	-0.042*
	(0.052)	(0.091)	(0.119)	(0.037)
δj,7[West Region]	-0.030	-0.291***	-0.183	0.505**
	(0.050)	(0.104)	(0.108)	(0.152)
Spatial factors				
Crime rate at LA level	0.0004	0.001	-0.001	0.0003
	(0.0005)	(0.001)	(0.001)	(-0.830)
Unemployment rate at ED level	0.002	0.004	-0.005	0.003
	(0.004)	(0.007)	(0.008)	(-0.580)
Average commuting time	-0.002	-0.003	0.003	0.002
	(0.002)	(0.004)	(0.005)	(0.720)
Population density at ED level	-0.001*	-0.002*	0.002*	0.0004
	(0.001)	(0.001)	(0.001)	(1.630)
Population change 1996-2002	-0.0003	-0.0004	0.001	0.0004
	(0.001)	(0.001)	(0.001)	(0.450)
January mean daily min temperature at ED level	-0.086***	-0.138***	0.167***	0.056***
	(0.026)	(0.039)	(0.048)	(0.018)
July mean daily max temperature at ED level	0.002	0.004	-0.004	-0.001
	(0.034)	(0.054)	(0.066)	(0.022)
Annual mean concentration of PM_{10} (micrograms per cubic meter)	0.005**	0.008**	-0.009**	-0.003*
	(0.002)	(0.004)	(0.004)	(0.002)
ED within 2 Km from a Seriously Polluted River	0.060	0.074*	-0.105	-0.029*
	(0.043)	(0.040)	(0.066)	(0.017)
Presence of a landfill in the respondent's ED	0.037	0.048	-0.067	-0.019
	(0.077)	(0.079)	(0.13)	(0.030)
Presence of a coastline in the respondent's ED	0.104	0.108**	-0.168*	-0.043**
	(0.071)	(0.044)	(0.094)	(0.020)
% of people speaking Irish at local authority level	-0.004	-0.006	0.007	0.002
	(0.005)	(0.008)	(0.009)	(0.003)
Voter turnout at ED level	-0.005***	-0.007***	0.009***	0.003***
	(0.001)	(0.002)	(0.003)	(0.001)
Observations	1358			

*Note: Robust standard errors adjusted for clustering at ED level in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

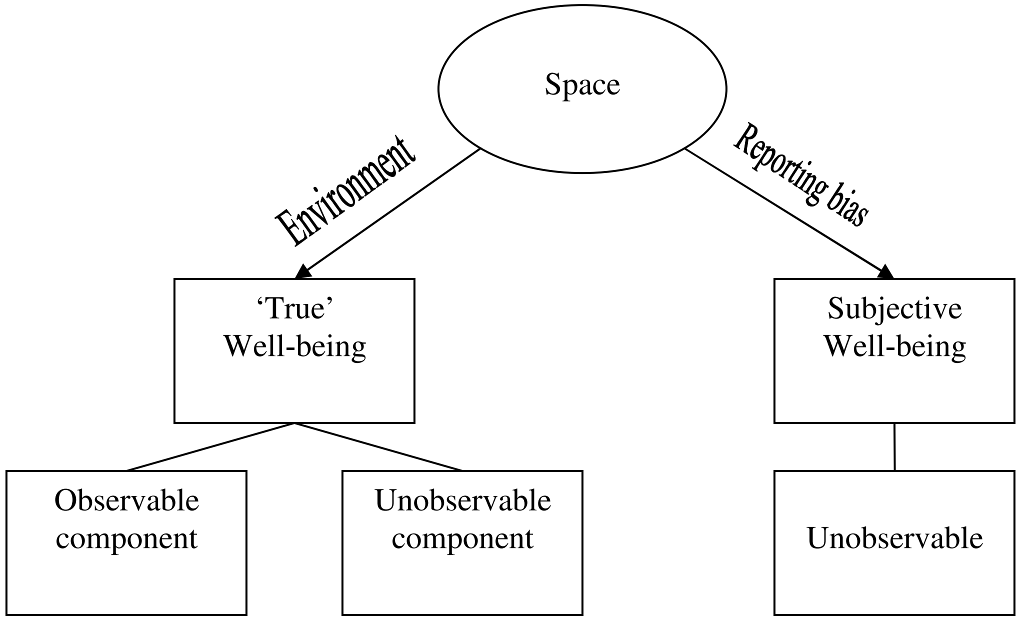


Fig. 1. The sources and forms of spatial heterogeneity

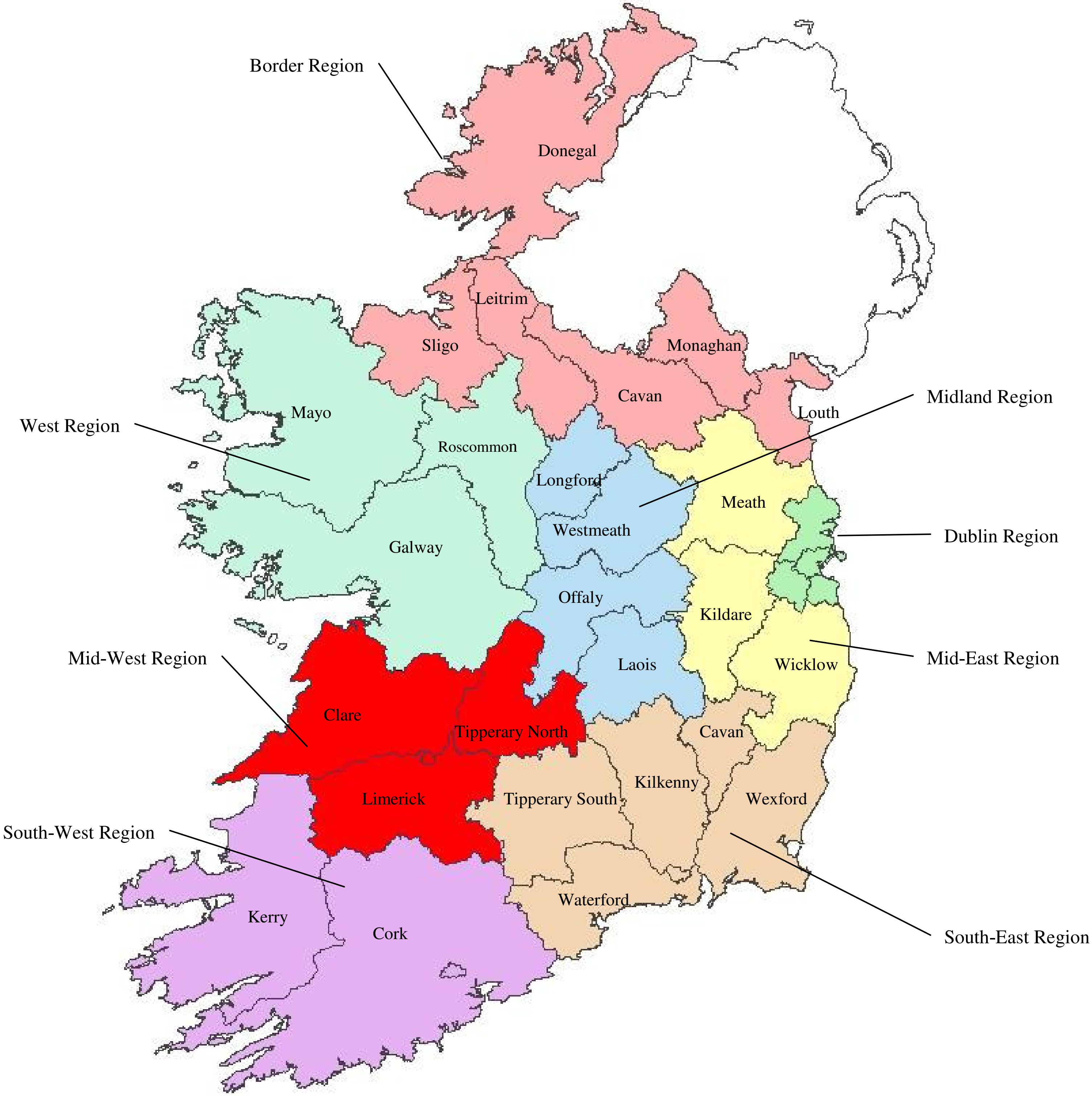


Fig. 2. The 8 regional authorities the Republic of Ireland and how they are subdivided into 34 local authorities

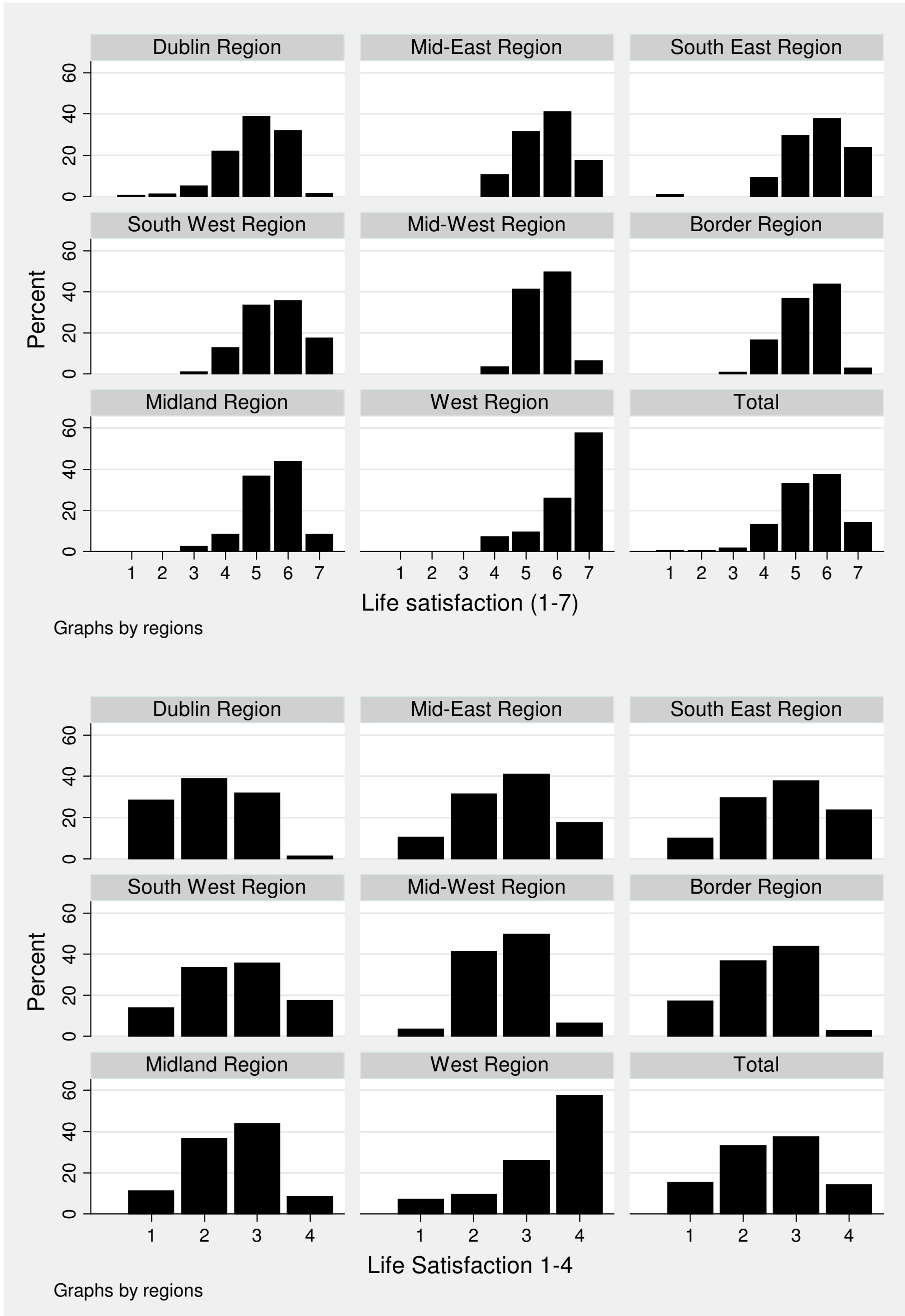
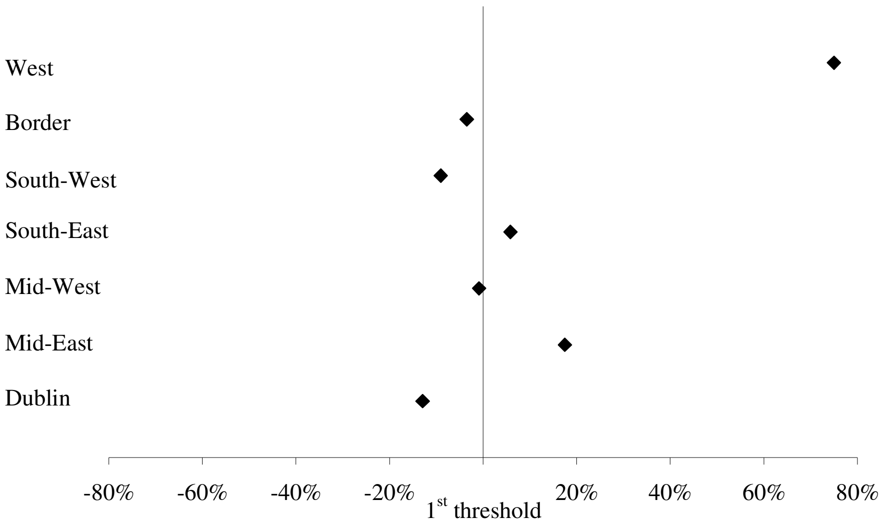
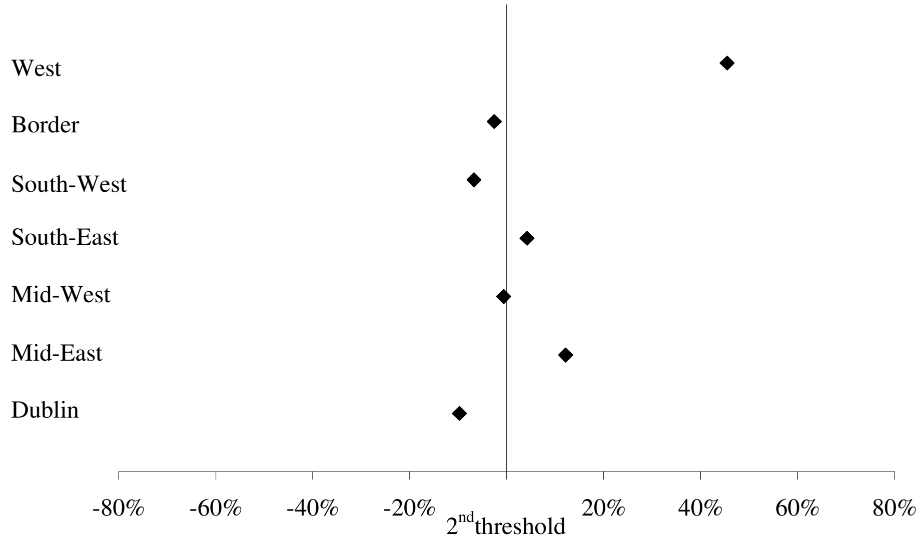


Fig.3. SWB by regions with 7 and 4 happiness categories
Note: 'Total' refers to the SWB scores at national level

Estimated reference scale at the first threshold



Estimated reference scale at the second threshold



Estimated reference scale at the third threshold

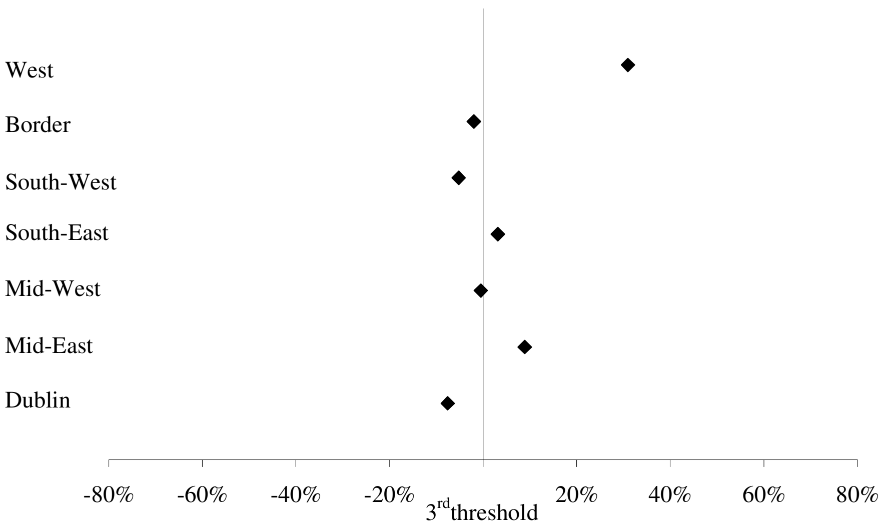


Fig 4. Estimated reference scale bias at each threshold

Appendix I

The parallel regression assumption

The parallel regression assumption or single index assumption is an implicit assumption underlines any standard ordinal model such as ordered logit or probit. This assumption seems to be overlooked by the practitioners when using ordinal models. A graphical way to show this is the following treatment adapted from Long and Freese (2005) and Winkelmann and Boes (2006).

The best way is to show how cumulative probabilities can be plotted in a graph where one independent variable is on horizontal axis and the probability is on the vertical axis. Let's suppose we have four outcomes (as in the paper) and one independent variable (x), then the structural model is:

$v = \alpha + \beta x + \varepsilon,$

hence the cumulative probabilities have three different thresholds:

$\Pr(SWB \leq 1| \, x) = \mathrm{F}(\mu_1 - \beta x)$
$\Pr(SWB \leq 2| \, x) = \mathrm{F}(\mu_2 - \beta x)$
$\Pr(SWB \leq 3| \, x) = \mathrm{F}(\mu_3 - \beta x)$

The cumulative probabilities can be plotted to visualise the parallel regression assumption as follows (Figure A1)

Figure A1 here

As it is evident, the probability curves have all the same shape and they are parallel. This comes from the fact that the parameters βs are equal for each equation, or in other words that the linear index βx is a common element in the argument of each cumulative probability (this is why some authors refer to it as single index assumption as well). The only difference among the cumulative probabilities depicted is that they are shifted to the right or the left in a parallel way. The shift is given by the difference between the thresholds.

This assumption limits the interpretation of the coefficients. On of the most important consequences is that the sign of the marginal effects are restricted to vary just once across the outcome categories. In other words, moving from the smallest SWB level (1 in our example) to the highest ($j = 4$), the marginal effects will be either first negative and then positive, or first positive to turn negative. This is illustrated by plotting the effects of discrete change of a variable on conditional density function of the error term ε ($f(\varepsilon|x)$) (Figure A2). The upper part shows the threshold mechanism behind ordered response models in terms of the error term. The density function has zero mean and is divided by 4 intervals and the thresholds are determined by $\mu_j - \beta x$. Any discrete change shifts the thresholds $\mu_j - \beta x$ to the left or the right (depending on the sign of both the discrete change and the parameter β). The lower part of the Figure shows a shift to the left. In this case the sign of the probability effects is negative when $j = 1, 2$, positive when $j = 4$ and ambiguous when $j = 3$.

Figure A2 here

The generalisation of the ordered logit model we have introduced here allows the parameters βs to differ at each threshold, such as:

$\Pr(SWB \leq 1 \mid x) = \mathrm{F}(\mu_1 - \beta_1 x)$
$\Pr(SWB \leq 2 \mid x) = \mathrm{F}(\mu_2 - \beta_2 x)$
$\Pr(SWB \leq 3 \mid x) = \mathrm{F}(\mu_3 - \beta_3 x)$

In this case the effects of discrete (or marginal) change are more flexible, they may vary across the distribution of the outcome and the sign can switch freely (compare equation (6) with (12)). For illustrative purposes, Figure A3 shows how discrete changes may look like on a conditional density function of the error terms in Gologit models.

Figure A3 here

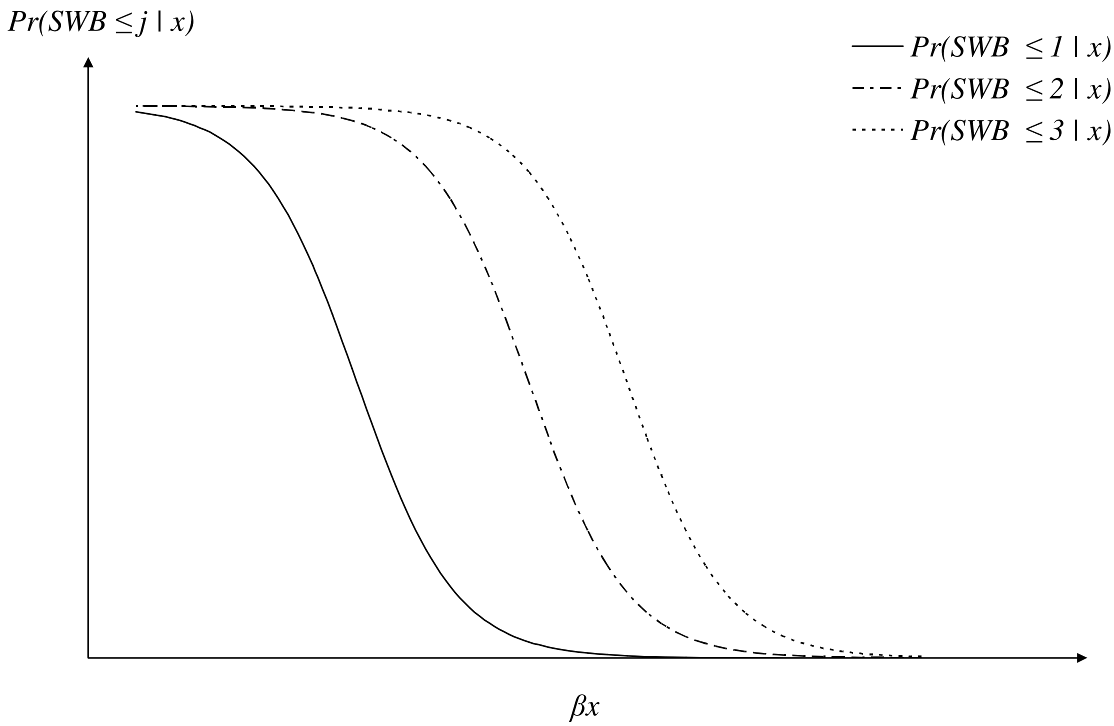


Fig. A1 Cumulative probabilities

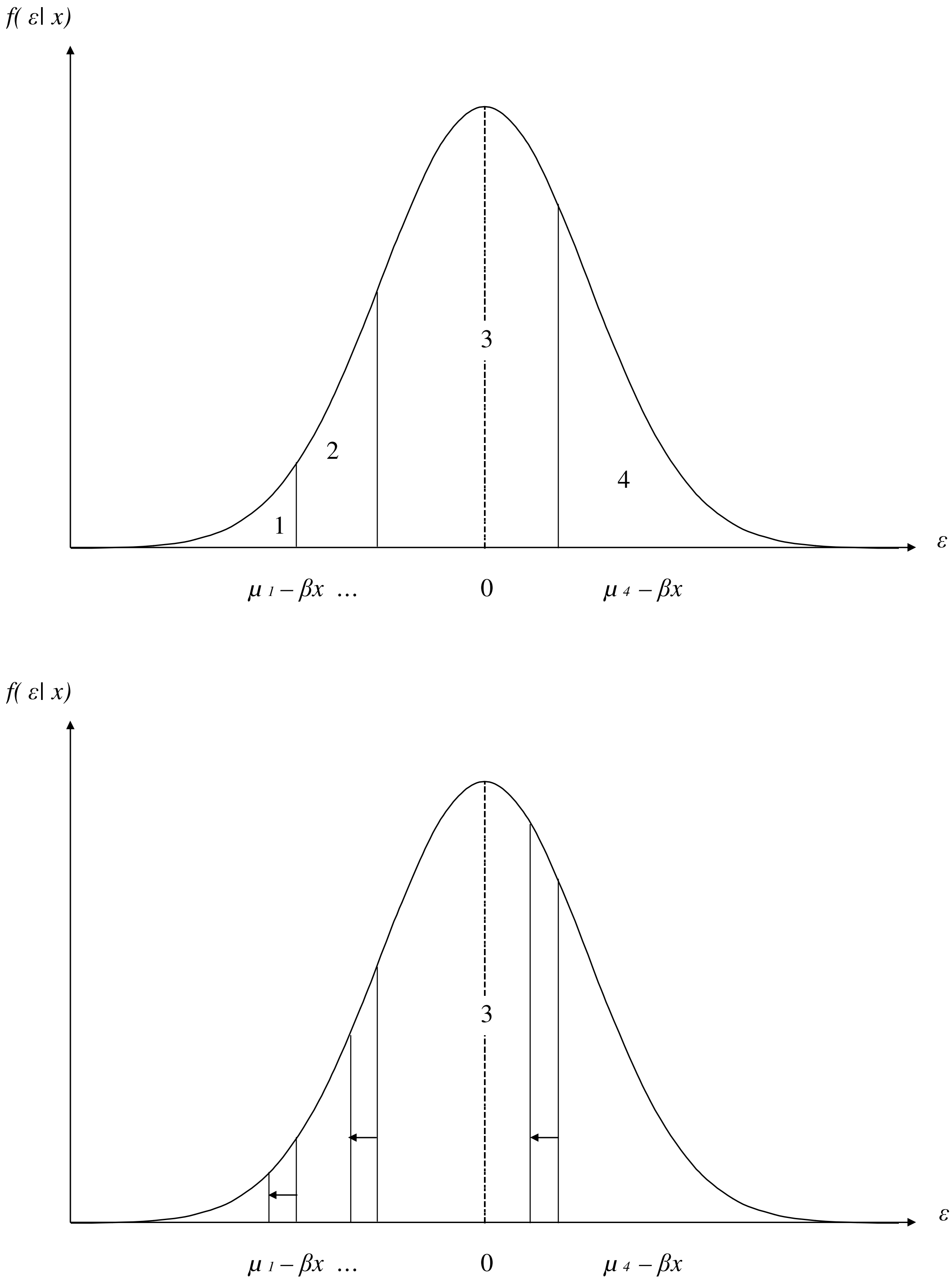


Fig. A2 The effect of probability changes on the density function of the error term

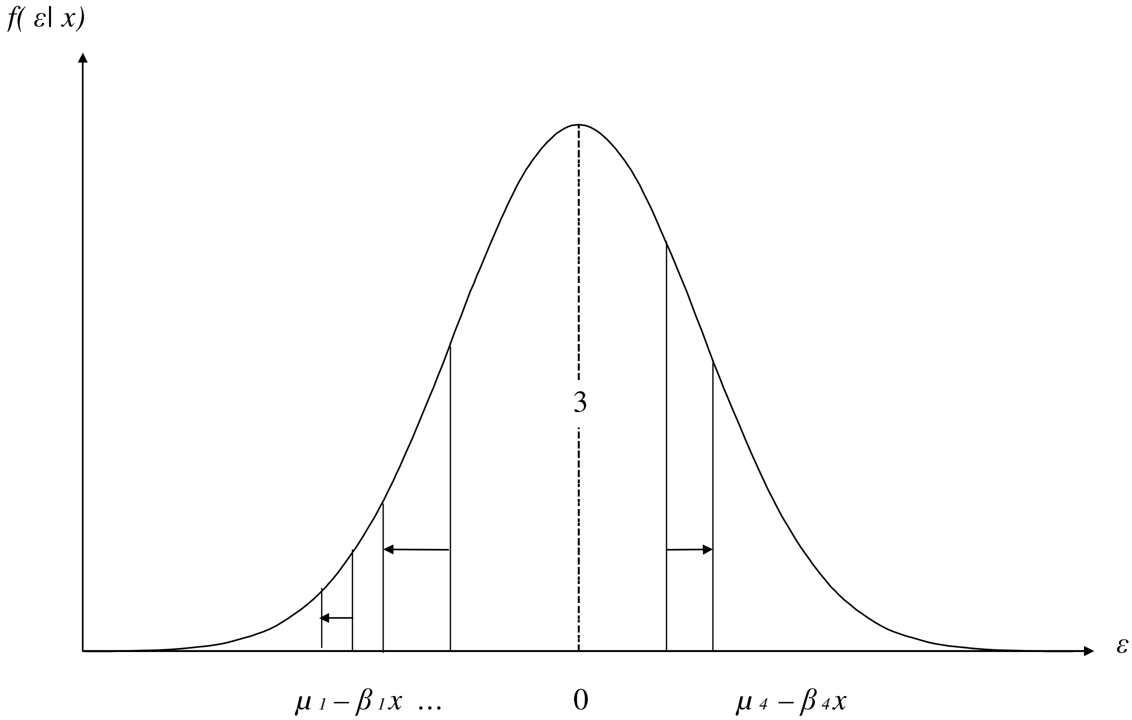


Fig. A3 The flexibility of the discrete changes in generalised ordered logit models

Appendix II

Table - Full set of parameters estimates - dependent variable: SWB (1 – 4)

	Ologit		*Gologit*	
Age	0.00747	0.00519	0.00519	0.00519
	(0.0065)	(0.0064)	(0.0064)	(0.0064)
Female	0.236	0.235	0.235	0.235
	(0.16)	(0.16)	(0.16)	(0.16)
Family size (number of components)	-0.0175	-0.0133	-0.0133	-0.0133
	(0.048)	(0.048)	(0.048)	(0.048)
Married	-0.391*	-0.222	-0.222	-0.222
	(0.23)	(0.23)	(0.23)	(0.23)
Cohabit	-0.481	-0.435	-0.435	-0.435
	(0.36)	(0.35)	(0.35)	(0.35)
Primary School	0.363	0.190	0.190	0.190
	(0.32)	(0.32)	(0.32)	(0.32)
Lower Secondary School	0.529*	0.301	0.301	0.301
	(0.28)	(0.29)	(0.29)	(0.29)
Upper Secondary School	0.269	0.148	0.148	0.148
	(0.18)	(0.19)	(0.19)	(0.19)
Log income	1.750***	2.153***	1.373***	0.125
	(0.50)	(0.53)	(0.51)	(0.58)
Self-employed	0.216	0.324	0.324	0.324
	(0.26)	(0.25)	(0.25)	(0.25)
Part-time	-0.230	-0.124	-0.124	-0.124
	(0.31)	(0.29)	(0.29)	(0.29)
Full-time	-0.0313	0.124	0.124	0.124
	(0.29)	(0.28)	(0.28)	(0.28)
Student	0.230	0.274	0.274	0.274
	(0.47)	(0.45)	(0.45)	(0.45)
Keeping House	-0.286	-0.243	-0.243	-0.243
	(0.29)	(0.26)	(0.26)	(0.26)
Unemployed	-1.321***	-1.212***	-1.212***	-1.212***
	(0.40)	(0.38)	(0.38)	(0.38)
Population density at ED level	0.00898	0.00983*	0.00983*	0.00983*
	(0.0055)	(0.0057)	(0.0057)	(0.0057)
Population change from 1996 to 2002	0.00306	0.00271	0.00271	0.00271
	(0.0058)	(0.0061)	(0.0061)	(0.0061)
Crime rate at LA level	-0.00208	-0.00414	-0.00414	-0.00414
	(0.0053)	(0.0050)	(0.0050)	(0.0050)
Unemployment rate at ED level	-0.0248	-0.0248	-0.0248	-0.0248
	(0.051)	(0.044)	(0.044)	(0.044)
Average commuting time at LA level	0.0218	0.0185	0.0185	0.0185
	(0.025)	(0.025)	(0.025)	(0.025)
January mean daily min temperature at ED level	0.991***	0.896***	0.896***	0.896***
	(0.27)	(0.25)	(0.25)	(0.25)
July mean daily max temperature at ED level	0.0269	-0.0231	-0.0231	-0.0231
	(0.38)	(0.35)	(0.35)	(0.35)
Annual mean concentration of PM_{10} (micrograms per cubic meter)	-0.0534**	-0.0491**	-0.0491**	-0.0491**
	(0.025)	(0.023)	(0.023)	(0.023)

ED within 2 Km from a Seriously Polluted River	-0.575*	-0.540	-0.540	-0.540
	(0.34)	(0.34)	(0.34)	(0.34)
Presence of a landfill in the respondent's ED	-0.402	-0.342	-0.342	-0.342
	(0.62)	(0.63)	(0.63)	(0.63)
Presence of a coastline in the respondent's ED	-0.878*	-0.868*	-0.868*	-0.868*
	(0.52)	(0.49)	(0.49)	(0.49)
Dublin Region	-0.679	-0.874	-0.575	-1.552**
	(0.48)	(0.73)	(0.53)	(0.73)
Mid East Region	0.897*	0.461	0.771	1.498**
	(0.47)	(0.68)	(0.47)	(0.76)
South West Region	-0.420	-0.833	-0.437	0.442
	(0.69)	(0.78)	(0.68)	(0.86)
South East Region	0.402	-0.146	0.202	1.215
	(0.55)	(0.70)	(0.49)	(0.76)
Mid West Region	0.0621	1.042	0.0896	0.117
	(0.55)	(0.90)	(0.54)	(0.86)
Border Region	-0.0829	-0.183	-0.0844	-1.083
	(0.45)	(0.62)	(0.48)	(0.95)
West Region	2.383**	0.469	1.594**	2.949***
	(0.94)	(0.73)	(0.73)	(0.85)
% of people speaking Irish at LA level	0.0492	0.0390	0.0390	0.0390
	(0.056)	(0.050)	(0.050)	(0.050)
Voter turnout at ED level	0.0489***	0.0473***	0.0473***	0.0473***
	(0.015)	(0.014)	(0.014)	(0.014)
Constant	-22.80**	-24.67***	-19.21**	-9.579
	(9.62)	(9.17)	(9.29)	(9.78)
Observations	1358	1358	1358	1358
Wald-Chi2	367.1	655.9		
Pseudo-R2	0.142	0.175		
Log pseudo-likelihood	-1522	-1463		

*Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*