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A longitudinal study of area-level deprivation in Ireland, 1991–2011

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Abstract. The diffusion of deprivation indices and their application in a wide variety of contexts raises a number of conceptual and methodological issues, particularly in relation to the analysis of change over time. We seek to address these issues by developing an aggregate-level theoretical approach which can guide the construction of a statistical model for enumeration districts in Ireland using five waves of census data (1991, 1996, 2002, 2006, 2011). We use a powerful and flexible family of statistical models—multiple-group mean and covariance structural equation modelling—to obtain comparable estimates of affluence and deprivation for each wave of data. The scores for the three component dimensions—referred to as demographic vitality, social class composition, and labour market situation—are mapped using GIS techniques, together with an overall measure of affluence and deprivation. Using the maps and other results we provide an original discussion of the sociospatial impacts of the economic boom in Ireland between 1996 and 2006, and the subsequent downturn. We highlight the importance of population flows and housing-market dynamics in understanding the nature of each phase and when evaluating the sustainability of economic growth.

Keywords: deprivation index, Ireland, census of population, structural equation modelling, multiple-group model, longitudinal research, aggregate-level analysis

1 Introduction: measures of deprivation

The aim of area-level indices of affluence and deprivation is to provide a robust composite measure of social conditions at the local level using geographical units with small and relatively homogeneous populations. These indices have many applications, including medical and epidemiological research on social gradients in health, health risks, and health-care outcomes (Bosma et al, 2001; Boyle et al, 2001; Davey Smith et al, 2001; Duncan et al, 1999; Eachus et al, 1996; Pickett and Pearl, 2001) and as a proxy for social class in research projects where such information is lacking at the individual level, but where it is possible to link individuals to small areas (Danesh et al, 1999; Galobardes et al, 2007). Deprivation indices are also used in other areas of research, including studies that rely on aggregate-level data on voting behaviour, consumption, educational qualifications, and labour-market participation (cf, Buck, 2001; Heath, 1999; Kalff et al, 2001).

The diffusion of deprivation indices and their application in a wide variety of contexts raises conceptual and methodological issues in relation to their construction and composition, including the issue of dimensionality (Curtin et al, 1996; Folwell, 1995), indicator selection (Coombes, 1995), transformations (Noble et al, 2006), and methods for obtaining overall estimates. We have discussed these issues in previous publications, emphasising the potential of structural equation modelling (SEM) techniques to provide satisfactory solutions to the principal challenges involved (Haase and Pratschke 2005; Pratschke, 2004; Pratschke and

Haase 2007). Other researchers have applied similar techniques to individual-level data related to deprivation (Tomlinson et al, 2008).

In this paper we focus on a key question in research on social deprivation: namely, the analysis of change over time. Many policy applications require scores for small areas which can be compared directly between different periods and across jurisdictions (cf Social Exclusion Unit, 2004). The comparability of scores makes it possible to use deprivation indices to explore the selective spatial impacts of specific processes, providing insights into the nature and effects of economic growth, for example, and the impact of recession. The availability of comparable scores for different European countries would make it possible to study area-level deprivation in border regions, compare different cities, and support EU policy making (cf, Haase et al, 2012).

We illustrate the analytical potential of comparable deprivation scores by studying the effects of economic growth in the Republic of Ireland between 1996 and 2006 and the subsequent economic crisis. Using data from five waves of the Census of Population for 1991, 1996, 2002, 2006, and 2011, we explore how the spatial distribution of affluence and deprivation was affected by growth and crisis over a twenty-year period. The intensity of both economic phases and the availability of harmonised census data at five-year intervals make Ireland a fascinating laboratory for studying longitudinal trends and temporal dynamics in area-level affluence and deprivation.

The rapidity with which the 2011 Census data were published by the Irish Central Statistics Office allows us to present a novel approach in this article, based on cutting-edge methodologies which are of undeniable relevance to other European countries where small-area data will be released at a later date. The potential applications of these methods are far reaching in the context of the simultaneous collection of harmonised census data in EU countries during 2011. The number and choice of indicators used reflect the aim of developing an index of affluence and deprivation with relatively modest data requirements. Applying statistical techniques using multiple-group structural equation models for the first time in the analysis of area-level deprivation, we show that it is possible to obtain a very well-fitting model with an invariant measurement structure.

2 Theoretical framework

In recent years the spatial articulation of social processes has received great attention from urban sociologists and social geographers. Similar trends are evident across many other disciplines, highlighting the widespread interest in theorising 'space' that emerged during the 1980s and 1990s. Methodologists who were involved in developing and applying multilevel modelling techniques were arguing during the late 1980s and early 1990s that 'space matters' (Jones et al, 1992), whilst epidemiologists were exploring the role of social context in relation to health inequalities (McCarron et al, 1994) and psychologists were discussing the influence of 'ecological niches' on child development (Bronfenbrenner, 1989). The result was to focus interdisciplinary attention on the spatial context of social phenomena and the ways in which the latter are structured.

These debates can contribute to the study of area-level affluence and deprivation by clarifying conceptual issues, suggesting potential mechanisms and identifying fertile areas of inquiry. In fact, sociospatial distributions may be viewed as the end result of interdependent and 'coevolving' processes, including the ways in which people are 'sorted into' and 'sorted out of' local areas, the material and symbolic resources that are owned and controlled by local populations, and their differential access to services, goods, leisure, and educational opportunities. Other factors include the spatial distribution of demand for labour at various levels of qualification, the relationships and interactions between people within and between areas, the built environment, and variations in the ways in which reproduction and childcare

are organised. A key social science challenge is to theorise the ways in which these sociospatial processes trigger adjustments and reactions across different domains and how they influence the distribution of social advantage and disadvantage.

When we use aggregate data to construct indices of affluence and deprivation, we should arguably draw on aggregate-level concepts and theories. Conversely, once we have identified the required indicators and indices, we can use these to refine our theories regarding the underlying social processes. The social class composition of an area is influenced by the quality of its built environment (existing houses, parks, and gardens), the quality of local services, and other factors. Well-connected and exclusive central locations are more attractive to those who can afford higher house prices. Demographic vitality is also influenced by location, as areas that are more isolated tend to experience higher levels of out-migration, and by factors such as the distance to third-level educational establishments, the local labour-market situation, the ethnic and migration background of the area, and its social class composition. The labour-market situation is determined by demand for labour within the local system, the ability of residents to access wider labour markets, the nature of social relationships within the area, the ethnic and migration composition of the area, and the educational attainments of local residents.

We are of the opinion that these three dimensions—social class composition, demographic vitality, and labour-market situation—are the main components of affluence and deprivation when measured at the aggregate level. Other possible dimensions include: (a) the quality of the built environment; (b) educational attainments; (c) house prices; (d) the quality of schools and services; (e) the social–relational fabric. The first three of these are related to social class composition, as we have defined it, implying that it may not be necessary to develop specific measures for these dimensions. The final two dimensions are more difficult to measure using existing data sources, but are of undeniable interest and relevance.

Each of these dimensions has a degree of temporal stability, whilst also influencing the values of the others, creating a spiral of mutually reinforcing relationships. Exogenous influences—such as the demand for labour or locational advantages—intersect this interdependent system, provoking adjustments and reactions. By analysing changes in the values of the related indicators we can estimate variations in the dimensional scores and consequently gain insights into the nature of the processes that determined these transformations.

3 Index of affluence and deprivation for enumeration areas

We now describe how the principal theoretical dimensions of affluence and deprivation are measured within our model. These dimensions were theorised on an a priori basis, guided by existing research on deprivation in different jurisdictions, as summarised in Pratschke and Haase (2007). Once we have described the model, we will use SEM software to assess its fit to the data and to obtain parameter estimates. The dimension 'demographic vitality' is measured using three variables: (1) the age-dependency rate (percentage of people aged under 15 years or over 64 years); (2) the percentage of people who completed their education without progressing beyond primary school; and (3) the percentage of families with children under 15 years of age which are headed by a lone parent. This dimension is closely related to the notion of 'opportunity deprivation', which expresses the difficulties that local populations face in accessing jobs, services, and facilities, and which, ceteris paribus, lead to higher rates of emigration.

The rationale for using these three variables relates mainly to the way in which emigration 'hollows out' the demographic structure of local communities, with the result that those who remain in declining areas tend to be older and to have lower levels of educational attainments. In Ireland, demographic decline has, almost exclusively, affected rural areas, and the percentage of lone parents is particularly low in these areas due to the relative absence of social housing. By contrast, areas of population growth, typically found in urban centres, are characterised by a larger proportion of young couples and tend to have a higher percentage of households headed by a lone parent.

The second dimension, 'social class composition', measures the social character of local areas and reflects the capacity of local residents to access material, social, and cultural resources. It is measured by three indicators, as the absence of resources manifests itself in: (1) a prevalence of low-skilled jobs amongst heads of household (small farmers are classified with semiskilled and unskilled occupations, whilst large farmers are included with higher professionals); (2) a high percentage of people with low educational qualifications; and (3) a relatively low percentage of higher professionals (cf Krieger et al, 1997; Marks, 2010; Shaw et al, 2001).

The third dimension reflects the capacity of local residents to access employment, regardless of their qualifications. We refer to this as the 'labour-market situation'. Access to appropriate forms of employment is measured by three indicators: (1) the percentage of economically active men who are unemployed, (2) the percentage of economically active women who are unemployed; and (3) the percentage of households with children aged 15 years and under which are headed by a lone parent. Areas with a relatively large number of lone-parent households tend to have a weaker labour-market situation, as lone parents are often excluded from paid employment due to the cost of childcare. It would be possible, in theory, to use long-term unemployment rates or the percentage of social housing as additional indicators, although the nonnormal distributions of these variables would create added complexity. Areas of concentrated unemployment are typically situated in urban areas, have a relatively unstable population, and contain a high percentage of social housing and lone-parent households.

Figure 1 shows the pattern of relationships between the three dimensions of affluence/deprivation and the seven indicators considered. The three dimensions are conceptualised as correlated latent variables, whilst the model controls for measurement error in the indicators (as indicated by the 'ε' variables situated to the left of the figure, which reflect measurement error and the variance due to the 'uniqueness' of each single indicator). Partly because of the complexity of the statistical model—embracing five waves of census data—we use

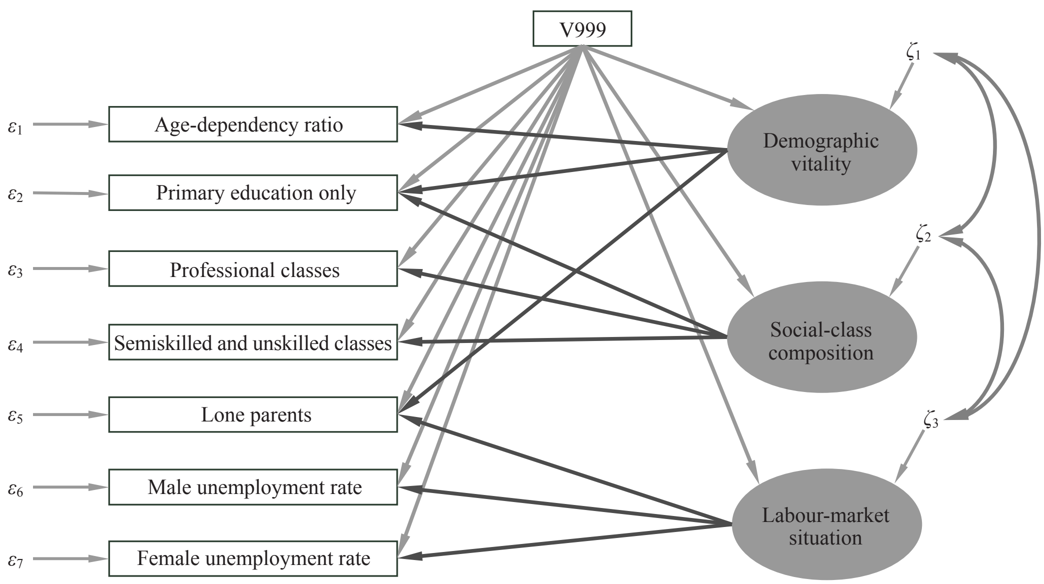

Figure 1. Hypothesised mean/covariance structure model of affluence and deprivation.

a relatively small number of indicators for each dimension. Although a larger number of variables would yield more stable estimates, the probability of obtaining satisfactory fit would be reduced. The overlaps between dimensions, which sometimes 'share' indicators, do not cause problems for the statistical model. The variable labelled V999 is a unit vector which represents the intercept in the regression equations and enables us to estimate the factor means using the SEM software package EQS 6.1 (Bentler, 2006). Because the dimensions and factors are regressed on this unit vector, they are dependent variables in the SEM model and consequently have a disturbance term (which is indicated by the 'ζ' variables to the right of the figure).

All three factors are measured on a continuous scale, tracing a quasi-normal curve with higher values coinciding with situations of affluence and lower values reflecting more severe deprivation. Thus, affluence and deprivation are conceptualised as opposing poles of a single distribution, and the overall deprivation score is calculated as the mean of the three dimensions once the latter have been centred on 0 (in 1991), divided by the standard deviation (for 1991) and multiplied by 10. Hence, the 1991 scores have a mean of 0 and a standard deviation of 10, whilst all subsequent changes in means and standard deviations are recorded relative to 1991.

4 The multiple-group structural equation model for means and covariances

The conceptual model of deprivation set out in the previous section is tested using SEM techniques with established statistical criteria. In statistical terms, SEM models place constraints on the joint distribution of a set of observed variables by omitting paths or correlations from the saturated model and by imposing equality constraints on parameters (Bentler, 2006). Consequently, the empirical adequacy of a SEM model can be assessed by measuring how well a sparse model reproduces the variance–covariance-means matrix of the observed indicators (Σ). The reproduced variance-covariance-means matrix [$\Sigma(\theta)$] depends on the free parameters estimated by the SEM model (Hayduk, 1987). Models with a smaller proportion of estimated parameters are generally more powerful, ambitious, and parsimonious, and this desirable characteristic is rewarded by the degrees of freedom (Mulaik, 2009). Equality constraints on equivalent parameters are used to obtain a uniform measurement model across waves, allowing us to estimate change over time in the mean of the factor scores.

The logic of multiple-group models is straightforward and involves estimating the parameters for two or more models simultaneously. These distinct models—each based on a different variance–covariance-means matrix—are combined to form a single more complex model. In our case the hypothesised conceptual model is constrained to have a stable structure across all five waves of census data; each wave of census data is associated with one of five submodels/groups. The only exception to this stability relates to the intercept for the percentage of people with low educational attainments, which is constrained for the periods 1991–96 and 2002–11, but free to vary between 1996 and 2002. The small change in the intercept registered here (the natural log of the centred values plus 40 increased from 3.71 to 4.10) may be due to the longer interval between these two waves of the census, but sensitivity analysis shows that it has a negligible influence on the results. The equality constraints placed on equivalent parameters in the various groups have the effect of fixing the measurement scale of the latent variables, rendering the model more parsimonious. By fixing the scale and ensuring factorial invariance, we can then compare the factor scores across waves (Meredith, 1993; Millsap and Meredith, 2004).

The resulting model is tested using the maximum-likelihood fitting function, with robust standard errors and indices of fit. Maximum-likelihood estimation is arguably the most appropriate, as the census variables are approximately multivariate normally distributed once appropriate transformations are applied. The goodness of fit of the model is assessed using the Hu–Bentler combined-fit criteria (Hu and Bentler, 1999), which is based on a decision rule that combines the comparative fit index (CFI) and the standardised root mean square residual (SRMR). Following this rule, the CFI must be above 0.95 and the SRMR must be equal to or less than 0.08 before a given model can be accepted. By relaxing just one equality constraint, we obtain satisfactory fit in the multiple-group SEM model, according to this rule.

5 Data

Small-area deprivation indices require data for entire populations, with a capillary coverage of the region or country to be analysed. For this reason, they are typically constructed using data from the Census of Population, population registers, or large administrative databases. The data used to estimate our multiple-group SEM model were derived from the aggregate results of the Irish Census of Population, with reference to 1991, 1996, 2002, 2006, and 2011 (the 2001 Census was deferred to 2002 as a result of measures to contain swine flu). The units of analysis were 3409 enumeration areas, with an average population of 1032 in 1991, reaching 1345 in 2011 (maximum 36057, minimum 73). Descriptive data for the indicators are given in appendix A. The transformations shown in table 1 were applied to the indicators with a view to rendering their distributions more approximately normal and ensuring that their variances were approximately equal, in order to facilitate convergence during estimation. The variable which measures educational attainments was centred due to the strong secular trend it displayed throughout the period in question, and was accompanied by a gradual 'depreciation' in the value of qualifications within the labour market

Table 1. List of variables and transformations.

Variable	Transformations
Age-dependency rate	Rescale (divide by 10)
Lone-parent households (%)	Add arbitrary constant (10) and take natural log
Low education (%)	Centre values, add an arbitrary constant (40) and take natural log
High professionals (%)	Rescale (divide by 10)
Low-skilled (%)	Add arbitrary constant (8) and take natural log
Male unemployment rate	Add arbitrary constant (3) and take natural log
Female unemployment rate	Add arbitrary constant (3) and take natural log

Table 2. Goodness of fit of the multiple-group structural equation modelling with structured means.

Measure of fit	Value
χ^2	5834.30 (84 degrees of freedom) (Significance < 0.00000)
Satorra–Bentler robust χ^2	5110.54 (84 degrees of freedom) (Significance < 0.00000)
Comparative fix index	0.96
Robust comparative fix index	0.97
Standardised root mean square residual	0.02
Root mean-square error approximation	0.11 (0.106, 0.113)
Robust root mean-square error approximation	0.102 (0.099, 0.106)

Table 3. Unstandardised coefficients and robust standard errors (in brackets) for multiple-group mean and covariance structure model.

Parameter	1991	1996	2002	2006	2011
Loading Demographic vitality → *Age dependency* (R^2 = 0.28–0.37)	−1.00	−1.00	−1.00	−1.00	−1.00
Loading Demographic vitality → *Primary education* (R^2 = 0.60–0.86)	−0.45 (0.01)	−0.45 (0.01)	−0.45 (0.01)	−0.45 (0.01)	−0.45 (0.01)
Loading Demographic vitality → *Lone parents* (R^2 = 0.30–0.45)	0.57 (0.01)	0.57 (0.01)	0.57 (0.01)	0.57 (0.01)	0.57 (0.01)
Loading Social class composition → *Primary education*	−0.20 (0.00)	−0.20 (0.00)	−0.20 (0.00)	−0.20 (0.00)	−0.20 (0.00)
Loading Social class composition → *Professionals* (R^2 = 0.74–0.83)	1.00	1.00	1.00	1.00	1.00
Loading Social class composition → *Low class* (R^2 = 0.71–0.80)	−0.28 (0.00)	−0.28 (0.00)	−0.28 (0.00)	−0.28 (0.00)	−0.28 (0.00)
Loading Labour-market situation → *Male unemployment* (R^2 = 0.70–0.85)	−1.00	−1.00	−1.00	−1.00	−1.00
Loading Labour-market situation → *Female unemployment* (R^2 = 0.29–0.39)	−0.70 (0.01)	−0.70 (0.01)	−0.70 (0.01)	−0.70 (0.01)	−0.70 (0.01)
Loading Labour-market situation → *Lone parents*	−0.34 (0.01)	−0.34 (0.01)	−0.34 (0.01)	−0.34 (0.01)	−0.34 (0.01)
Intercept *Age dependency*	3.99 (0.01)	3.99 (0.01)	3.99 (0.01)	3.99 (0.01)	3.99 (0.01)
Intercept *Lone parents*	2.87 (0.01)	2.87 (0.01)	2.87 (0.01)	2.87 (0.01)	2.87 (0.01)
Intercept *Primary education*	3.71 (0.01)	3.71 (0.01)	4.10 (0.01)	4.10 (0.01)	4.10 (0.01)
Intercept *Professionals*	2.29 (0.02)	2.29 (0.02)	2.29 (0.02)	2.29 (0.02)	2.29 (0.02)
Intercept *Low class*	3.55 (0.01)	3.55 (0.01)	3.55 (0.01)	3.55 (0.01)	3.55 (0.01)
Intercept *Male unemployment*	2.84 (0.01)	2.84 (0.01)	2.84 (0.01)	2.84 (0.01)	2.84 (0.01)
Intercept *Female unemployment*	2.60 (0.01)	2.60 (0.01)	2.60 (0.01)	2.60 (0.01)	2.60 (0.01)
Variance Demographic vitality	0.09 (0.01)	0.10 (0.01)	0.08 (0.01)	0.08 (0.01)	0.06 (0.00)
Variance Social class composition	0.80 (0.01)	0.79 (0.03)	0.76 (0.03)	0.71 (0.02)	0.71 (0.03)
Variance Labour-market situation	0.17 (0.01)	0.19 (0.01)	0.16 (0.01)	0.15 (0.01)	0.10 (0.00)
Intercept/Mean Demographic vitality	0.0	0.15	0.63	0.59	0.46
Intercept/Mean Social class composition	0.0	0.24	0.69	0.98	1.11
Intercept/Mean Labour-market situation	0.0	0.09	0.51	0.54	−0.30
Covariance Demographic vitality ↔ Social class composition	0.15 (0.01)	0.10 (0.01)	0.04 (0.01)	−0.06 (0.01)	−0.06 (0.01)
Covariance Demographic vitality ↔ Labour-market situation	−0.003 (0.003)	−0.02 (0.004)	−0.02 (0.00)	−0.04 (0.00)	−0.03 (0.00)
Covariance Social class composition ↔ Labour-market situation	0.25 (0.01)	0.27 (0.01)	0.24 (0.01)	0.25 (0.01)	0.22 (0.01)

6 Results

The fit of the multiple-group SEM model with structured means is summarised in table 2. The χ^2 is not statistically significant, mainly due to the large number of observations, which has the effect of inflating small discrepancies (Fan et al, 1999). However, the CFI is highly satisfactory and, in conjunction with the SRMR, suggests a very well-fitting model. Table 3 contains all unstandardised coefficients and associated standard errors. All coefficients are statistically significant ($\alpha = 0.05$), with the exception of the covariance between demographic vitality and labour-market situation in 1991.

Scores for the three dimensions were obtained for each wave of data using the generalised least square factor scores procedure in EQS 6.1 (Bentler, 2006). Table 4 summarises these scores, using the means obtained from the SEM model and dividing the scores for each dimension by the standard deviation in 1991. Table 5 summarises the resulting index scores (calculated as the mean of the three component dimensions).

Table 4 shows that the standard deviation of two of the latent variables—demographic vitality and (particularly) labour-market situation—decreased significantly between 2006 and 2011. It is interesting to observe that demographic vitality closely follows the economic cycle, increasing rapidly from 1996 to 2002, as large numbers of working-age migrants arrived in Ireland, and declining over the following decade, with increasing speed after 2006.

Table 4. Trended dimension scores.

	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Demographic vitality 1991	−33.79	60.94	0.00	10.00	0.76	1.81
Demographic vitality 1996	−31.06	55.81	3.68	10.38	0.37	0.92
Demographic vitality 2002	−25.39	68.10	15.69	10.27	0.09	1.04
Demographic vitality 2006	−48.82	68.01	14.69	10.30	0.17	1.78
Demographic vitality 2011	−25.54	56.79	11.51	9.06	0.10	1.07
Social class composition 1991	−25.81	46.20	0.00	10.00	0.93	2.02
Social class composition 1996	−22.66	50.84	2.49	9.97	0.89	2.00
Social class composition 2002	−20.80	49.64	7.22	9.74	0.75	1.51
Social class composition 2006	−21.33	47.62	10.29	9.63	0.32	0.96
Social class composition 2011	−17.51	51.37	11.67	9.92	0.56	1.20
Labour-market situation 1991	−29.66	42.81	0.00	10.00	0.09	0.47
Labour-market situation 1996	−31.10	42.43	2.08	10.61	−0.01	0.14
Labour-market situation 2002	−26.92	50.42	11.42	10.71	−0.18	0.32
Labour-market situation 2006	−28.79	50.78	12.23	10.66	−0.24	0.41
Labour-market situation 2011	−31.42	41.24	−6.72	7.99	0.22	0.41

Table 5. Overall trended index scores.

	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Index of deprivation 1991	−21.68	30.85	0.00	7.32	0.62	1.18
Index of deprivation 1996	−20.57	33.54	2.75	7.40	0.38	0.56
Index of deprivation 2002	−17.73	40.33	11.44	7.30	−0.06	0.08
Index of deprivation 2006	−25.13	33.58	12.40	6.94	−0.17	0.33
Index of deprivation 2011	−14.14	32.14	5.48	6.22	0.38	0.52

By its very nature, social class composition is less sensitive to short-term trends, but nevertheless reflects the intensity of the boom in 1996–2002. The positive trend in the mean of this latent variable is mainly due to the long-term expansion of non-manual occupations, qualified employment, and managerial positions at the expense of low-skilled manual jobs. As social class composition is measured with reference to the respondent's most recent job, it is not influenced directly by the economic cycle or by unemployment. The results shown in table 4 strongly suggest that demographic trends played a fundamental role in the boom, as well as registering the hidden costs of the subsequent crisis.

The relative equilibrium between demographic vitality, social class composition, and labour-market situation which prevailed during the early years of the boom was under increasing strain in 2002–06, even before the crisis manifested itself. The levelling-off of improvements in the labour-market situation was accompanied by a sharp reversal in demographic vitality, signalling a structural weakness which exacerbated the effects of the subsequent international downturn. The decline of immigration and the return of selective emigration following 2006 gave rise to an enormous drain in human capital and a depletion of central-age cohorts. As this loss is not captured by standard economic and social indicators, it is important to show how deprivation measures can benchmark social and economic development over time.

Although the immediate causes of the crisis were international, its disastrous impact in Ireland had its roots in the unsustainable nature of the preceding boom, which is evidenced by the opposing trends of demographic vitality and labour-market situation between 2002 and 2006. In spatial terms, this contradiction manifested itself, inter alia, in a rapid extension of the commuter belt around the main urban areas during the boom. Moving further from the city, the social composition of commuter towns was weaker and house prices (relatively) more accessible. However, their distance from sources of employment, poor local infrastructure, the weakness of internal social relations, and the relative lack of opportunities made these communities rather fragile. This fragility became immediately apparent with the onset of recession. The maps in figure 2 show these changes using comparable, trended deprivation scores (in order to facilitate the presentation of results) for the area around the capital city. (All data for 1991–2011 are available online at http://www.trutzhaase.eu.)

For 1991 [figure 2(a)] the polarised nature of Dublin, on the right, is clearly evident, with a sharp north–south divide running through the centre of the city and extensive areas of deprivation (shaded dark grey) to the north (Ballymun, Finglas), northwest (Blanchardstown), West (Ballyfermot, Clondalkin), and southwest (Tallaght, Walkinstown). By contrast, the most affluent neighbourhoods were found in the south (extending from the centre of the city as far as the borders of County Wicklow), including the commuter belt of Dublin to the north (Kinsealy, Malahide), west (Maynooth, Naas), and south (Bray, Enniskerry).

By 1996 [figure 2(b)] an improvement was already visible in social conditions in the outskirts of the city, with the formation of a relatively affluent commuter belt. Over the next six years, the economic boom had a powerful impact, and consequently the constant measurement scale loses its power to discriminate within the commuter belt. A large part of the central city was gentrified, leaving pockets of deprivation to the north of the city and to the northwest, west, and southwest of County Dublin.

Only small changes are evident between 2002 [figure 2(a)] and 2006 [figure 2(b)], involving shifts in the relative position of specific neighbourhoods and the effects of massive ongoing investment in the city centre. By 2011 [figure 2(e)], however, the relative decline of the more remote commuting towns was apparent, whilst more central areas generally retained their affluent character. The situation was radically different from that observed in 1991, and substantially less deprived in practically all areas (particularly in the city centre). However, when deprivation scores are fully standardised for each wave of data, the stability of relative scores across Ireland is striking.

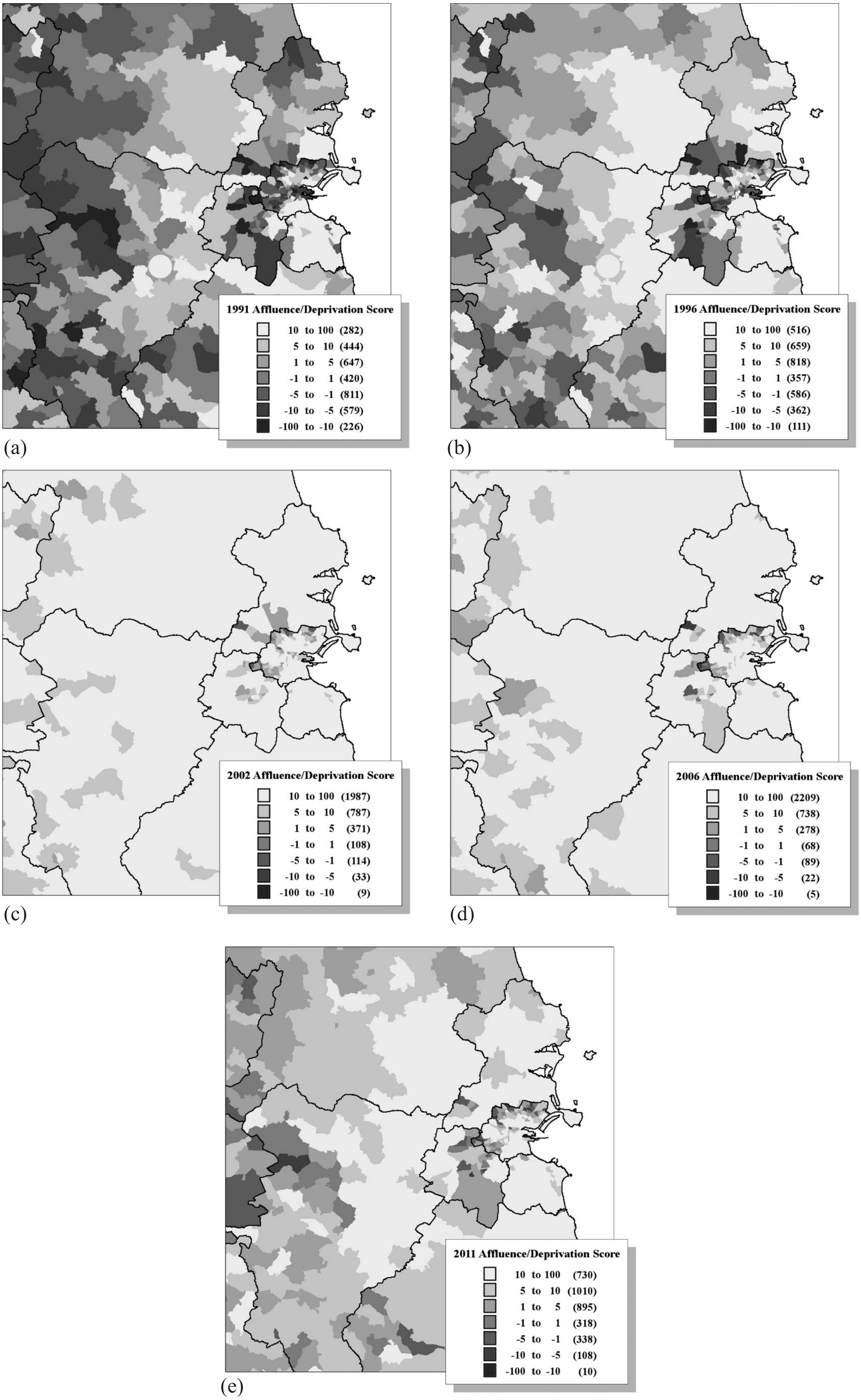

Figure 2. Thematic map of affluence and deprivation in enumeration districts of Dublin City and surrounding areas for the years: (a) 1991; (b) 1996; (c) 2002; (d) 2006; (e) 2011.

7 Conclusions

In the first part of this paper we developed an innovative theoretical approach to the analysis of area-level affluence and deprivation inspired by new trends in the analysis of aggregate-level spatial processes. The most important element of this approach is the way in which it grounds the empirical study of deprivation in an understanding of aggregate-level processes. This leads to a multidimensional approach which follows the traces that these processes leave in the observed characteristics of local areas and the populations that reside within them. When analysed in cross-sectional terms, the dimensions of deprivation should be allowed to correlate, reflecting their interdependence over time and the ways in which they are influenced by common causes. Perhaps the most appropriate way of conceptualising these complex intertemporal relationships is in terms of a spiral or helix, which reflects the stability of each dimension as well as the lagged, reciprocal causal effects between them. Exogenous influences cut across this spiral in different ways, influencing the means of the dimensions and their distributions.

An empirical analysis was carried out using multiple-group mean and covariance SEM. The results show that it is possible to achieve excellent fit when applying these techniques to aggregate-level data from the Census of Population. An attractive feature of this approach is that it enables us to develop a theoretical model, fix its structure, and then test its fit to the data, thus ensuring that the dimensions of deprivation included in the analysis are precisely those envisaged by the researcher. By constructing a robust set of measures at five-year intervals over a twenty-year period, it is possible to gain considerable insights into the relationship between aggregate-level processes and area-level deprivation. By comparing the five maps of deprivation scores, it is possible to achieve a better understanding of the changing distribution of affluence and deprivation at the local level.

The results reveal a systematic change in the covariance between demographic vitality and social class composition, which declined from 0.15 in 1991 to 0.04 in 2002, reaching −0.06 in 2011 (table 3), implying a correlation of 0.55 in 1991, 0.14 in 2002, and −0.31 in 2011. Thus, these dimensions were quite strongly and positively correlated at the beginning of this twenty-year period but had a moderate negative correlation at the end, whilst all other coefficients remained relatively stable. As the scale and sociological substance of these variables was held constant by the equality constraints, the results suggest a significant change in the configuration of multidimensional deprivation.

Demographic processes were initially linked to social class in Ireland, due to both reciprocal causation and shared determinants. Reciprocal causal effects are plausible, implying that in the late 1980s lower class neighbourhoods and small farming areas were exposed to a greater risk of demographic decline, whilst emigration led to a further weakening of their social class composition due to ‘brain drain’. This coincides with what we know about the sociodemographic trends affecting rural Ireland during the period in question (Curtin et al, 1996). Intense economic growth during the years of the ‘Celtic Tiger’ interrupted this process, fuelling population growth in almost all areas of the country. The positive effects of the boom, including labour shortages, rising house prices, and higher public spending infused into all areas, creating new opportunities which helped to stabilise the population of rural areas that had previously experienced decline.

This unprecedented, exogenous influence led to an “uncoupling” of demographic processes from endogenous social class composition, which is reflected in the weak correlation between demographic vitality and social class composition in 2002 (0.14). This correlation had already turned negative in 2006 (−0.23), implying that changes were once again occurring towards the end of the boom. As national population growth continued at a high level, increasing by roughly 300 000 people in each of the three intervals (1996–2002, 2002–06, and 2006–11), we conclude that the reason for this change lies with the way in which this growth was distributed at the *regional* and *local level*.

Essentially, our argument is that inflated house prices during the boom encouraged first-time buyers (in particular) to purchase homes in lower class urban neighbourhoods or in rural areas that were situated at a considerable (and growing) distance from the main urban centres. At the start of the boom, demographic growth was most apparent in relatively attractive and sought-after residential locations, but once house prices in these areas became unaffordable, the same processes provoked growth in the less affluent areas. The intensity of the boom, the massive increase in population, constant housing shortages, and the real-estate 'bubble' created a cascading aggregate-level process whereby progressively more deprived neighbourhoods were targeted by first-time buyers who were desperate to enter the housing market. In spatial terms, this process drove the incremental extension and expansion of the commuter belt around the urban areas.

The collapse of the housing market and the onset of recession did not reverse this process, as purchasing power and borrowing capacity declined as rapidly as house prices. As the relative affluence of the outer rings of the commuting system declined, many people who had moved there became 'stranded', trapped by negative equity and other factors. There are indications that families with lower mortgage repayments are gradually moving back to the city (often to rented accommodation) with the aim of reducing their costs and improving their access to employment and other opportunities (O'Brien, 2013). In the absence of countervailing effects, these more distant parts of the commuter belt appear destined to experience pronounced demographic decline in coming years.

The study of aggregate-level sociospatial processes has the potential to develop further in coming years by pushing out the research frontier in three main directions. The first direction involves comparative research, drawing particularly on the rich 2011 Census in European countries. The techniques illustrated in this article could be applied to other European countries or groups of countries, with the benefit of shedding light on the distribution of affluence and deprivation in border regions and facilitating the assessment of cross-border initiatives. The second direction entails the construction of new indicators relating to the education system, access to services and opportunities, the quality of the built environment, migration patterns, and the social fabric of local communities. The inclusion of additional indicators and dimensions has the potential to shed light on the finer distinctions between areas that have a similar socioeconomic profile but a different residential history. Finally, there is scope for innovation in relation to statistical analysis techniques, integrating latent growth curves, latent classes, and multilevel structures, for example, in the dynamic analysis of deprivation. These techniques could be used to construct new typologies, to identify emergent forms of disadvantage and to compare trajectories of change over time.

As we have shown, the longitudinal analysis of aggregate-level affluence and deprivation in Ireland reveals the sociospatial fragility of the economic boom and the enormous difficulties involved in managing intense and rapid economic and demographic growth. At the same time, these spatially differentiated effects underline the crucial role of deprivation indices not only in identifying areas of social need, but also in understanding the nature of the aggregate-level processes which most strongly influence the distribution of affluence and deprivation at the local level.

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Appendix

Table A1. Descriptive data for indicators 1991–2011.

	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
1991 indicators						
Age-dependent rate	1.32	6.49	4.06	0.50	−0.72	1.72
Percentage lone parents	2.30	4.22	2.84	0.31	0.48	0.95
Percentage of low education	−0.62	4.30	3.63	0.38	−2.58	12.69
Percentage of professionals	0.07	6.72	2.28	0.99	0.89	1.61
Percentage of low skilled	2.40	4.59	3.58	0.30	−0.47	0.96
Male unemployed rate	1.10	4.23	2.84	0.46	−0.01	0.25
Female unemployed rate	1.10	4.24	2.65	0.55	−0.73	1.19
1996 indicators						
Age-dependent rate	1.14	6.01	3.76	0.48	−0.53	2.09
Percentage lone parents	2.30	4.61	2.93	0.36	0.56	0.97
Percentage of low education	2.07	4.34	3.64	0.32	−1.31	2.78
Percentage of professionals	0.19	7.31	2.57	0.98	0.85	1.65
Percentage of low skilled	2.36	4.41	3.48	0.29	−0.53	1.12
Male unemployed rate	1.10	4.32	2.75	0.48	0.06	0.23
Female unemployed rate	1.10	4.18	2.54	0.52	−0.57	0.81
2002 indicators						
Age-dependent rate	0.79	5.46	3.46	0.48	−0.74	2.89
Percentage lone parents	2.30	4.70	3.01	0.39	0.53	0.62
Percentage of low education	2.71	4.36	3.66	0.24	−0.60	0.78
Percentage of professionals	0.26	7.15	2.94	0.96	0.72	1.37
Percentage of low skilled	2.30	4.27	3.38	0.27	−0.52	1.13
Male unemployed rate	1.10	4.21	2.34	0.46	0.21	0.44
Female unemployed rate	1.10	3.89	2.26	0.46	−0.31	0.49
2006 indicators						
Age-dependent rate	0.85	5.00	3.38	0.47	−0.99	3.42
Percentage lone parents	2.30	4.44	3.16	0.39	0.30	0.26
Percentage of low education	2.95	4.33	3.67	0.21	−0.24	0.34
Percentage of professionals	0.26	6.89	3.29	0.95	0.29	0.86
Percentage of low skilled	2.27	4.20	3.27	0.26	−0.19	0.64
Male unemployed rate	1.10	4.08	2.27	0.45	0.20	0.37
Female unemployed rate	1.10	3.65	2.23	0.44	−0.30	0.57
2011 indicators						
Age-dependent rate	0.82	5.08	3.49	0.46	−1.38	5.21
Percentage lone parents	2.30	4.44	3.19	0.39	0.17	0.26
Percentage of low education	3.10	4.31	3.67	0.18	0.06	0.28
Percentage of professionals	0.41	7.19	3.37	0.98	0.46	0.97
Percentage of low skilled	2.34	4.08	3.24	0.25	−0.30	0.79
Male unemployed rate	1.10	4.23	3.15	0.33	−0.17	0.53
Female unemployed rate	1.10	3.98	2.76	0.38	−0.42	1.40