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Annals of the American Association of Geographers

ISSN: 2469-4452 (Print) 2469-4460 (Online) Journal homepage: http://www.tandfonline.com/loi/raag21

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To cite this article: Leo Kavanagh, Duncan Lee & Gwilym Pryce (2016): Is Poverty Decentralizing? Quantifying Uncertainty in the Decentralization of Urban Poverty, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2016.1213156

To link to this article: http://dx.doi.org/10.1080/24694452.2016.1213156

Is Poverty Decentralizing? Quantifying Uncertainty in the Decentralization of Urban Poverty

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In this article we argue that the recent focus on the suburbanization of poverty is problematic because of the ambiguities and inconsistencies in defining suburbia. To improve transparency, replicability, and comparability, we suggest that research on the geographical changes to the distribution of poverty should focus on three questions: (1) How centralized is urban poverty? (2) To what extent is it decentralizing? (3) Is it becoming spatially dispersed? With respect to all three questions, the issue of quantifying uncertainty has been underresearched. The main contribution of the article is to provide a practical and robust solution to the problem of inference based on a Bayesian multivariate conditional autoregressive (CAR) model, made accessible via the R software package CARBayes. Our approach can be applied to spatiotemporally autocorrelated data and can estimate both levels of and change in global relative centralization index (RCI), local RCIs, and dissimilarity indexes. We illustrate our method with an application to Scotland's four largest cities. Our results show that poverty was centralized in 2011 in Glasgow, Dundee, and Aberdeen. Poverty in Edinburgh, however, was decentralized: Nonpoor households tend to live closer to the center than poor ones and increasingly so. We also find evidence of statistically significant reductions in centralization of poverty in all four cities. To test whether this change is associated with poverty becoming more dispersed, we estimate changes to evenness and local decentralization of poverty, revealing complex patterns of change. *Key Words: deprivation, inference, segregation, suburbanization, urban poverty.*

我们于本文中主张，晚近对于贫穷郊区化的关注是有问题的，因为对郊区的定义模糊且不一致。为了促进透明度、可复製性以及可比较性， 我们主张， 有关贫穷分佈的地理变迁之研究必须聚焦以下三大问题：(1) 城市贫穷的集中程度为何？(2) 城市贫穷的去中心化程度为何？(3) 贫穷是否在空间上越来越分散？在上述三大问题方面，对于量化不确定性的问题之研究皆有所不足。本文的主要贡献是对根据贝叶斯多变量条件自迴归 (CAR) 模型所进行的推断之问题，提供实际且强健的解决方法，并且能够透过R套装软件 CARBayes 获得。我们的方法能够应用至时空自相关的数据，并且能够同时评估全球相关的集中化指标 (RCI)、地方 RCIs，以及相异的指标之程度与变化。我们将该方法应用至苏格兰的四大城市来进行解说。我们的研究显示，在 2011 年，格拉斯哥、邓迪和亚伯丁的贫穷是集中的。但在爱丁堡，贫穷却是去中心化的：非贫穷的家户较贫穷家户更倾向居住于较为靠近市中心的地区，且此趋势正逐渐上升。我们同时发现四个城市中的贫穷集中现象在统计上显着化约的证据。为了检定此一变迁是否与贫穷变得更为分散有关，我们评估贫穷的平均和地方去中心化的改变，揭露了改变的复杂模式。 *关键词： 剥夺，推断，隔离，郊区化，城市贫穷。*

En este artículo argüimos que el reciente énfasis en la suburbanización de la pobreza es problemático debido a las ambigüedades e inconsistencias que se observan en la definición de los suburbios. Para mejorar la transparencia, capacidad de duplicación y comparabilidad, sugerimos que la investigación sobre los cambios geográficos en la distribución de la pobreza se concentre en tres cuestiones: (1) ¿Qué tan centralizada está la pobreza urbana? (2) ¿En qué grado está aquella descentralizándose? (3) ¿Está tornándose espacialmente dispersa? Respecto de las tres preguntas, el aspecto de cuantificar la incertidumbre ha sido poco investigado. La principal contribución del artículo es proveer una solución práctica y robusta al problema de la inferencia con base en un modelo Bayesiano condicional autorregresivo (CAR) multivariado, accesible a través del paquete de software R CARBayes. Nuestro enfoque puede aplicarse a datos autocorrelacionados espacio-temporalmente, y puede calcular los niveles y cambios en el índice de centralización relativa global (RCI), los RCIs locales y los índices de disimilitud. Nuestro método lo ilustramos con una aplicación a las cuatro ciudades más grandes de Escocia. Nuestros resultados muestran que la pobreza estaba centralizada en 2011 en Glasgow, Dundee y Aberdeen. Sin embargo, la pobreza estaba descentralizada en Edimburgo. Los hogares sin pobreza tienden a vivir más cerca del centro que los pobres, tendencia que es cada vez más aguda. También hallamos evidencia de reducciones estadísticamente significativas en la centralización de la pobreza en todas las cuatro ciudades. Para comprobar si este

Annals of the American Association of Geographers, 0(0) 2016, pp. 1–13
Initial submission, February 2016; revised submission, May 2016; final acceptance, May 2016
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cambio está asociado con una mayor dispersión de la pobreza, calculamos los cambios de la uniformidad y la descentralización local de la pobreza, revelando patrones complejos de cambio. *Palabras clave: privación, inferencia, segregación, suburbanización, pobreza urbana.*

The location of poor households near the center and wealthier households in the suburbs was for a long time seen as the archetypal social structure of the industrial city, famously stylized by Burgess (1925) as concentric zones around the central business district (CBD). The question of whether poverty is moving away from the inner cities to the periphery (Lupton 2011; Rogers and Mulholland 2012; Hunter 2014; Kneebone and Berube 2013) not only challenges this long-standing characterization but touches on a number of important policy issues. For example, achieving multineighborhood welfare provision is arguably more difficult to achieve if poverty is dispersed or clustered in distant pockets around the periphery. Decentralization of poverty might also reduce its visibility, leading to pockets of adversity hidden from public view (Jargowsky 2003; Kneebone and Berube 2013), and might have a deleterious effect on access to employment (Thakuriah 2011; Gibb, Osland, and Pryce 2014). These multidimensional consequences might add new layers of complexity to identifying the most socially just and economically efficient way to provide welfare, transport, and infrastructure investment.

Decentralization of poverty, however, might also have its benefits. For example, if there are particularly adverse neighborhood effects associated with inner-city ghettos, perhaps decentralization of poverty will help ameliorate some of those effects. There could be potentially beneficial reductions in exposure to air pollution if poor households are moving away from central areas with greatest congestion and air pollution. Decentralization of poverty might also suggest greater access to suburban amenities such as green space (Wolcha, Byrneb, and Newellc 2014) and good quality schooling (Lleras 2008). There might also be implications for urban political economy and the spatial balance of power within the city region, counteracting some of the governance issues associated with wealthy households drifting ever further from the center (e.g., Galster 2014).

These consequences all suggest that the decentralization of poverty is of sufficient importance to warrant careful measurement. This article seeks to address three key questions in this respect. First, how can we measure the process of decentralization in a transparent and replicable way? We propose adopting a measure developed in the ethnic segregation literature—the relative centralization index (RCI)—applied both globally (at the city level) and locally (at the neighborhood level).

Second, how can we know that an apparent change in the pattern of poverty is statistically significant rather than the artefact of random measurement error or population churn? This is an important issue that has not been given sufficient attention in the literature. A key contribution of our article, therefore, is to provide a robust method for inference for measuring the uncertainty associated with changes to the RCI based on a Bayesian multivariate conditional autoregressive (CAR) model.

Third, if poverty is decentralizing, is it also becoming less spatially concentrated, or are inner-city enclaves of poverty merely being replaced by outer-city ones? This is highly relevant not only for the provision of welfare services but for some of the neighbourhood effects mechanisms that assume or rely on spatial concentration (Galster 2007; Manley et al. 2013). Folch and Rey (2016) demonstrated how relative centralization measures can be usefully applied to capture local spatial concentration. Again, though, as far as we are aware, robust statistical inference has yet to be developed for measuring changes to the local centralization of poverty. A third goal of this article is thus to measure the dispersion of poverty and again provide robust statistical inference using Bayesian multivariate CAR methods.

The article is structured as follows. We first review the literature on suburbanization of poverty. We then propose a methodological strategy for answering the three basic research questions described earlier in a way that is robust and that maximizes the potential for intercity comparison. We then illustrate our approach using data on four Scottish cities. We conclude with a brief summary and directions for future research.

Literature

In much of the recent literature, changes to the spatial pattern of poverty have been couched in terms of suburbanization. Research on the United States by the Brookings Institution, for example, has highlighted the rise of suburban poverty as one of the most significant trends in U.S. cities. Kneebone and Berube (2013) described "a series of communities in transition . . . from outposts of the middle class to symbols of modern American poverty" (172). Suburbia is now "home to the largest and fastest-growing poor population in the country and more than half of the metropolitan poor" (172–74). Between 2000 and 2010, "the number of poor individuals living in the suburbs of the nation's largest metropolitan areas rose by more than half (53 percent) . . . more than twice the rate of increase in cities" (Kneebone and Berube 2013, 504–5).

In the United Kingdom, the most detailed study to date of suburbanization of poverty is the report by the Smith Institute (Hunter 2014). Finding very strong evidence for surbanization of poverty in England and Wales, Hunter (2014) confirmed that the trend is not an exclusively U.S. phenomenon. We are aware of no equivalent published research on Scotland, although related issues of spatial concentration of poverty are explored in some detail in Rae (2012a, 2012b).

Although this emerging literature has raised important issues, there are a number of significant problems with the methods used. Defining the decentralization of poverty in terms of suburbanization is problematic because there is no unambiguous definition of *suburban*. It is difficult to ascertain where the inner city ends and the suburb starts, and different researchers use different rules to make what are essentially arbitrary judgments that could have profound effects on the results (and could be manipulated with impunity to achieve the desired findings). The definition used by Kneebone and Berube (2013), for example, "represents a compromise that distinguishes within each metropolitan area between large, broadly recognized jurisdictions and smaller places that are more likely to lack the scale and capacity necessary to address some of the challenges of rising poverty" (449). There is no obvious point along this trade-off between "recognized jurisdictions" and "sufficient scale" that researchers can be guaranteed to unanimously subscribe to, so there is a very considerable scope for arbitrariness and incompatibility across studies.

Hunter (2014) used house type as a key criteria, defining suburbs as having a lower incidence of flats and terraced housing than urban areas and higher population density than rural areas. Again, there is no clear justification for using this particular definition and no clear cut-point in terms of a universally accepted mix of house types that constitutes suburbia. How many flats does an area need before it ceases to be suburban? Why use flats as a defining criterion? It is not obvious why type of housing construction should define how one measures the spatial distribution of poverty. Dwelling type does not in itself indicate housing quality. Flats can be luxurious or rundown, large or small, and surrounded by extensive grounds or crowded by other dwellings.

A further problem is that the composition of housing can change over time, which makes intertemporal comparison (one of the goals of this article) all the more complex and ambiguous. For example, large houses might be converted to flats as average family size declines, and retirement flats could be constructed in areas previously dominated by low-density detached houses. In what sense do such changes make a neighborhood less suburban? The task of researchers using a suburbanization approach is made all the more precarious because any attempt to justify a particular choice of definition on the basis of social or policy criteria leaves them in danger of conflating the outcome measure (spatial distribution of poverty) with causal factors (changes in demographics and housing demand that might affect changes in dwelling types).

It also places additional burdens on the data and makes it more difficult to make the analysis consistent over time. Using Hunter's approach, one needs to have extensive data on changes to the housing stock, because this could change the boundaries of the areas designated as suburban. If these boundaries change over time, one has the problem of not comparing like with like: Even if the spatial distribution of poverty remains constant, poverty will appear to be more or less suburbanized just because of the changes to the pattern of suburbia, defined by some arbitrary criteria. The more dimensions to the definition of decentralization and the more demands placed on the data, the more difficult it will be to replicate measures across cities and the more difficult it will be to compare results.

A more transparent approach would be to measure decentralization based on the spatial relationship of impoverished households to the center of the city. Such measures already exist, developed in the ethnic segregation literature to gauge the extent to which ethnic minority households were concentrated near the city center (Duncan and Duncan 1955; Massey and Denton 1988). Curiously, there has been no recent work that we are aware of that applies centralization indexes to UK data on poverty and no consideration anywhere in the literature, as far as we are aware, to issues of statistical inference for estimates of change in decentralization indexes (see later). One explanation is that that citywide decentralization measures have fallen out of favor because of the polycentric nature of twenty-first-century employment, and because of the reliance on "local knowledge . . . to identify the centre" (Folch and Rey 2016). Centralization measures remain a useful measure, however, not least because they offer a simple, transparent, and replicable measure well suited to intercity comparison and can be a useful way to monitor changes to city structure. Also, sensitivity analysis (as demonstrated later) can be used to ascertain whether the results are sensitive to the definition of the center (in our case, not). Relative measures such as the RCI are particularly appealing because they are not dependent on defining particular boundaries between the inner city and suburbia (as in the absolute centralization index; Massey and Denton 1988). Instead, the RCI is based on ordering aerial units by distance from the city center and measures relatively whether people in poverty or not in poverty are more centralized.

- RCI = 0: The two groups (poor and nonpoor) have the same spatial distribution in terms of distance to the city center.
- RCI > 0: People in poverty tend to be closer to the city center than people not in poverty.
- RCI < 0: People in poverty tend to be further away from the city center than people not in poverty.

The measure was first proposed by Duncan and Duncan (1955) and is included in the widely read review by Massey and Denton (1988), which includes it as a measure of minority centralization, one of their five dimensions of segregation along with evenness, exposure, concentration, and clustering. Folch and Rey (2016) recently proposed the RCI as a local measure, applied to each and every aerial unit, to give a moving window of the locus of relative position of one group relative to another. The RCI does not replace the richness of bespoke suburbanization approaches. Rather, it should be viewed as a complementary method that will bring a more comparable transparent dimension to research on the spatial distribution of poverty.

Uncertainty

Another overlooked problem associated with the suburbanization of poverty literature is the quantification of uncertainty. How do we know whether an apparent shift in the suburbanization of poverty is not simply an outcome of random events (e.g., population churn) or measurement error (particularly problematic if suburban boundaries are also changing)? In the context of ethnic residential mix, Folch and Rey (2016) provided a simple procedure for estimating whether a particular RCI value is statistically different to zero. This is essentially a distance from randomness measure, and does not help us address the question of whether observed change over time is statistically significant.

As far as we are aware, none of the extant studies monitoring the suburbanization or decentralization of poverty, or indeed of ethnicity, have provided robust estimates of statistical significance such as confidence intervals. Development of robust inference is frustrated by two key factors. The first is spatial autocorrelation in the data, which frustrates the computation of standard errors. Simple bootstrapping methods are likely to be highly misleading (Lee, Minton, and Pryce 2015). The second challenge is how to devise a method that provides robust inference for change in the RCI, rather than simply computing confidence intervals for individual RCI values. Both of these challenges are addressed later.

Finally, having established whether poverty is decentralizing or not, an obvious question is to ask whether it is becoming more dispersed. Suppose, for example, that poverty is moving away from the inner cities; it is potentially important to understand whether it is regrouping in peripheral pockets or dispersing among more affluent neighbors. Measuring changes to the evenness of poverty across aerial units is typically measured using the dissimilarity index (DI). Folch and Rey (2016) also proposed using the RCI as a local measure of segregation. We apply both methods here and address the respective issues of inference. Lee, Minton, and Pryce (2015) recently proposed a method for estimating credible intervals (the Baysesian equivalent of confidence intervals) for the DI in particular periods, and there have been recent developments in using Bayesian methods to uncover signal from noise in multilevel models of segregation (Jones et al. 2015; Manley et al. 2015). There is currently no assessment of significant change over time in either the DI or the global and local RCI, however. Therefore here we develop a Bayesian multivariate CAR model to develop suitable significance assessment methods via 95 percent uncertainty intervals for both the DI and the local RCI.

Data and Methods

The study region is a single city (here we consider Aberdeen, Dundee, Edinburgh, and Glasgow) that has been partitioned into n nonoverlapping data zones (Flowerdew, Feng, and Manley 2007; see also http://www.gov.scot/Publications/2005/02/20697/52626). For each city, data are available for each of two census years, 2001 and 2011, from the Scottish Neighbourhood Statistics database (http://www.sns.gov.uk), and interest is in identifying any change in the centralization of poverty over time in each city. For census year j ($j = 1$ [2001] and $j = 2$ [2011]), the prevalence of poverty is quantified for the kth data zone by (Y_{kj}, N_{kj}), which, respectively, denote the number of people in poverty in the kth data zone in the jth census year and the total number of people in that data zone. The data zones have been ordered in terms of distance from the city center, so that data zone $k = 1$ is the closest to the city center and $k = n$ is the furthest data zone from the city center. Thus the complete ordered spatial data for all n data zones are denoted by $\mathbf{Y} = (\mathbf{Y}_1, \ldots, \mathbf{Y}_n)$ and $\mathbf{N} = (\mathbf{N}_1, \ldots, \mathbf{N}_n)$, respectively, where $\mathbf{Y}_k = (Y_{k1}, Y_{k2})$ and $\mathbf{N}_k = (N_{k1}, N_{k2})$. The estimated raw proportion of people in poverty in the kth datazone and jth census year is thus $\hat{p_{kj}} = Y_{kj}/N_{kj}$ and can be used to compute the RCI as follows:

$$\mathrm{RCI}_j = \sum_{i=2}^{n} a_{i-1j} b_{ij} - \sum_{i=2}^{n} a_{ij} b_{i-1j}.$$

Here (a_{ij}, b_{ij}) are, respectively, the cumulative numbers of people in poverty and not in poverty in the closest i units from the city center in census year j; that is,

$$a_{ij} = \left(\sum_{k=1}^{i} Y_{kj}\right) / \left(\sum_{k=1}^{n} Y_{kj}\right)$$

and

$$b_{ij} = \left(\sum_{k=1}^{i} N_{kj} - Y_{kj}\right) / \left(\sum_{k=1}^{n} N_{kj} - Y_{kj}\right).$$

The RCI can be computed as given for the raw data $(\mathbf{Y}, \mathbf{N})$ separately for each census year, but this approach has a number of problems. First, this produces an RCI as a single point estimate and is not accompanied by an associated measure of uncertainty. This is problematic for identifying statistically significant changes in centralization over time as highlighted in the previous section, because any observed changes might just be a result of random variation in the data and not a true change over time. Additionally, the data $(\mathbf{Y}, \mathbf{N})$ could contain recording or transcription errors. An extended discussion of these points can be found in Leckie et al. (2012). Additionally, the sample proportion $\widehat{p_{kj}} = Y_{kj}/N_{kj}$ is the maximum likelihood estimator of the true proportion p_{kj} from the simple model $Y_{kj} \sim \mathrm{Binomial}(N_{kj}, p_{kj})$, which assumes the observations are independent. It has long been noted, however, that spatial data such as these exhibit spatial autocorrelation, which is consistent with the "first law of geography" that "everything is related to everything else but near things are more related than distant things" (Tobler 1970, 236). This spatial autocorrelation should be accounted for when modeling the data, otherwise the results are invalid. Furthermore, the percentages of people in poverty in a data zone are correlated between the two years, and this temporal within-data-zone autocorrelation should also be accounted for. Therefore, in the next section we propose a model for these data that accounts for these two sources of autocorrelation and show how you can use it to produce a point estimate and 95 percent uncertainty interval for the RCI for each city. The joint modeling of both time periods allows us to further compute a point estimate and 95 percent uncertainty interval for the difference in the RCI between the two years.

A Spatial Model for the Data

Motivated by the preceding discussion and extending the work of Lee, Minton, and Pryce (2015), we propose modeling the data with a bivariate binomial generalized linear mixed model, which allows for spatial autocorrelation in the data, allows for temporal autocorrelation between the two census years, and enables us to quantify uncertainty in our estimated RCI. We take a Bayesian approach to analysis as is common in modeling spatial areal unit data (see Banerjee, Carlin, and Gelfand 2004; Bivand, Pebesma, and Gómez-Rubio 2008), and this allows us to compute the posterior distribution for the RCI, from which a point estimate (posterior median) and a 95 percent credible interval (the Bayesian equivalent of a 95 percent confidence interval) can be obtained. The Bayesian model we use has a likelihood specification given by

$$Y_{kj} \sim \mathrm{Binomial}(N_{kj}, p_{kj}) \quad k = 1, \ldots, n, \quad j = 1, 2$$
$$\ln\left(\frac{p_{kj}}{1 - p_{kj}}\right) = \beta_0 + \phi_{kj}.$$

The estimated proportion of people in poverty in area k in census period j, p_{kj}, is modeled on the logit scale by an overall intercept term β_0 and a separate random effect ϕ_{kj} for each data zone and census year. The set of spatial random effects for all data zones is denoted by $\phi = (\phi_1, \ldots, \phi_n)$, where $\phi_k = (\phi_{k1}, \phi_{k2})$ denotes the pair for the kth data zone for both census years. Spatial dependence is incorporated into these random effects via a binary n by n neighborhood matrix $\mathbf{W}$, where w_{ki} denotes whether data zones (k, i) are spatially close. Here we set $w_{ki} = 1$ if data zones (k, i) share a common border, and $w_{ki} = 0$ otherwise, with $w_{kk} = 0$ for all k. Based on this we model the random effects with the kronecker product of the CAR model proposed by Leroux, Lei, and Breslow (1999) that induces spatial autocorrelation (based on $\mathbf{W}$) and a between-census-year conditional covariance matrix $\boldsymbol{\Sigma}$. The vector ϕ is modeled as

$$\phi \sim \mathrm{N}\left(0, \left[\mathbf{Q}(\mathbf{W}, \rho) \otimes \sum{}^{-1}\right]^{-1}\right),$$

where spatial autocorrelation is induced via the precision matrix

$$\mathbf{Q}(\mathbf{W}, \rho) = \rho[\mathrm{diag}(\mathbf{W1}) - \mathbf{W}] + (1-\rho)\mathbf{I}.$$

This is a multivariate CAR (MCAR) prior, and is similar to that proposed by Gelfand and Vounatsou (2003). Such models are typically specified in their conditional form; that is, as a series of distributions for ϕ_k conditional on the remaining random effects. This conditional distribution is given by

$$\phi_k \mid \phi_{-k} \sim \mathrm{N}\left(\frac{\rho\sum_{i=1}^{n} w_{ki}\phi_i}{\rho\sum_{i=1}^{n} w_{ki} + 1 - \rho}, \frac{\sum}{\rho\sum_{i=1}^{n} w_{ki} + 1 - \rho}\right).$$

Here ϕ_{-k} denotes the set of random effects except the kth. The conditional expectation is a weighted average of the random effects in neighboring data zones, and the covariance is weighted by the number of neighboring data zones. Here ρ is a spatial dependence parameter, with ρ close to one corresponding to strong spatial dependence in the data and $\rho = 0$ corresponding to independence in space. We note that this formulation implies the same level of spatial dependence (same value of ρ) for each census year, but this simplification could be relaxed if needed (for details, see Gelfand and Vounatsou [2003] and the wider MCAR literature). Relaxing this assumption, however, increases model complexity unnecessarily, and we justify it for our data in the next section. Weakly informative priors are assigned to the remaining parameters, which is uniform (0, 1) for ρ, inverse-Wishart (3, I) (where I is the identity matrix) for the covariance matrix $\boldsymbol{\Sigma}$, and $N(0, 1000)$ for the intercept term β_0. We note that this prior specification for ρ rules out negative values corresponding to negative spatial autocorrelation, but this is rarely seen in practice in spatial areal unit data as discussed by Tobler, and the exploratory Moran's I analysis later shows our data exhibit positive spatial autocorrelation.

Inference for this model is based on Markov chain Monte Carlo (MCMC) simulation, which is conducted in R and available for others to use via the *MVS.CARleroux()* function in the CARBayes software (Lee 2013). The final results in the next section are based on M = 2,000 post-burn-in and thinned MCMC iterations, from which 2,000 samples $(\boldsymbol{p}_1, \ldots, \boldsymbol{p}_n)$ were obtained from the sampled values of the other parameters (where $\boldsymbol{p}_k = (p_{k1}, p_{k2})$). From each of these 2,000 samples the RCI was computed, resulting in the posterior distribution of the RCI being summarized by 2,000 values. The median and 2.5 and 97.5 percentiles were then computed, yielding a point estimate and a 95 percent credible interval for the RCI, using a similar approach to that described in Lee, Minton, and Pryce (2015). Furthermore, the posterior median and 95 percent credible interval were computed for the difference in RCI between the two census years to examine the existence of a significant change over time. This Bayesian approach to computing a segregation index was shown in Lee, Minton, and Pryce (2015) to perform well for the DI and, in particular, was vastly superior to a simple bootstrapping approach similar to that used by Brulhart and Traeger (2005), which does not allow for the spatial autocorrelation in the data.

Application to Scottish Cities

Data and Study Design

As previously outlined, data zone-level data were collected for two census years, 2001 and 2011, for the four largest cities in Scotland, namely, Aberdeen, Dundee, Edinburgh, and Glasgow. Data zones were chosen as the unit of analysis because they are the finest spatial scale at which we were able to obtain the benefit claimant data. Each data zone has between 500 and 1,000 residents. We define the boundaries of each city as all data zones that are in the larger health board region encompassing each city (Grampian, Tayside, Lothian, and Greater Glasgow and Clyde) and have a population density of more than 1,000 people per square mile. This results in the following number of data zones for each city: Aberdeen, 251; Dundee, 191; Edinburgh, 558; and Glasgow, 1,161.

We consider three measures of poverty, the percentages of people in each data zone that are in receipt of job seekers allowance (JSA), incapacity benefit (IB), and income support (IS).

- *Job seekers allowance* is the main benefit available to unemployed workers actively seeking employment. JSA "replaced Unemployment Benefit and Income Support (IS) for unemployed people from 7 October 1996" (Browne and Hood 2012, 16).
- *Income support* is paid to people on low incomes who are not seeking work. "Since its introduction in 1988, Income Support has been the main benefit available to those who are out of work but not seeking employment (and hence not eligible for Unemployment Benefit/JSA)" (Rutherford 2013, 7). IS is "mainly payable to lone parents with a child under 5 and carers" (Browne and Hood 2012, 22).
- *Incapacity benefit* is "payable to individuals who cannot work due to sickness or disability" (Browne and Hood 2012, 73).

These three means-tested benefits are typically paid to working-age people, which in 2001 included men aged sixteen to sixty-five and women aged sixteen to sixty, whereas in 2011 it had been standardized to ages sixteen to sixty-five for both sexes. Together, these benefits are likely to give a fairly comprehensive account of where the poorest households of working age live in each of the four cities in our study. For each of the three benefits, we have two years of data (2001 and 2011) on the total number of working age people (as defined earlier) in each data zone and the total number of people claiming the benefit.

The sample proportion of people in receipt of JSA in 2011 is shown for each city in Figures 1 to 4, and the maps corresponding to the other benefits and year are similar and are not shown. Their similarity is evidenced by the range of correlation coefficients between each sample proportion across the four cities for all benefits and years, which range between 0.687 and 0.956. Two data zones were removed from Glasgow because they had a zero working-age population in 2011. The proportions of people in poverty in each figure appear to exhibit spatial autocorrelation (smoothness), because areas that are close together typically exhibit similar

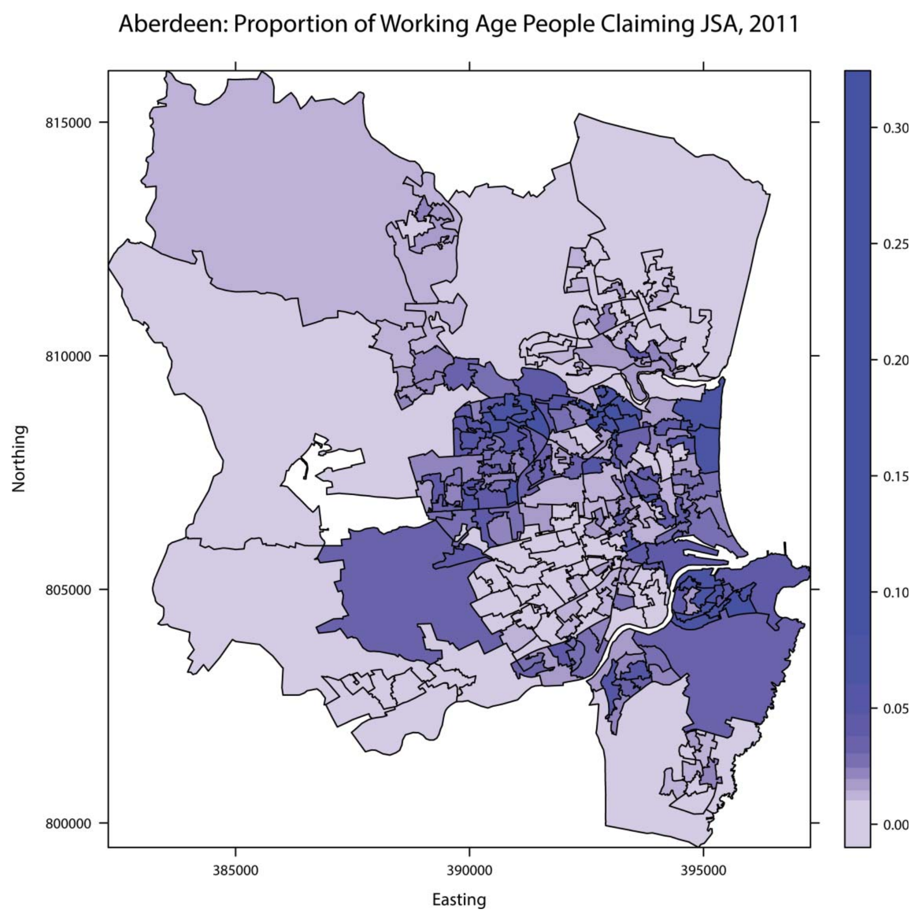

Figure 1. Proportion of people in receipt of job seekers allowance in 2011 in Aberdeen. JSA = job seekers allowance. (Color figure available online.)

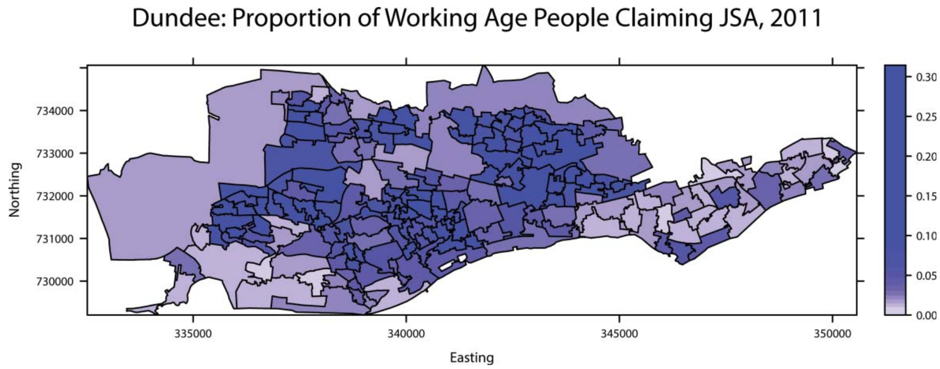

Figure 2. Proportion of people in receipt of job seekers allowance in 2011 in Dundee. JSA = job seekers allowance. (Color figure available online.)

proportions. This visual description is corroborated by statistically significant Moran's I statistics (Moran 1950) at the 5 percent level for each city, which are: Aberdeen, 0.504 (p = 0.00009); Dundee, 0.440 (p = 0.00009); Edinburgh, 0.442 (p = 0.00009); Glasgow, 0.453 (p = 0.00009). The p values here relate to a Monte Carlo permutation test (based on 10,000 random permutations of the data), where the null hypothesis is independence in space. The spatial autocorrelation present in JSA in 2011 was also present in 2001, for which the corresponding Moran's I statistics are Aberdeen, 0.453 (p = 0.00009); Dundee, 0.390 (p = 0.00009); Edinburgh, 0.382 (p = 0.00009), and Glasgow, 0.497 (p = 0.00009). These values are very similar to those for 2011, which validates our choice of a common spatial autocorrelation parameter ρ between the two years in the MCAR model. This similarity is repeated for the other benefits but the results are omitted for brevity. Thus the spatial models described here are appropriate because the data contain substantial spatial autocorrelation.

Model Implementation

Inference for each model was based on 2,000 MCMC samples, which were obtained by generating 40,000 samples, removing the first 20,000 as the burn-in period, and then thinning by ten to reduce the autocorrelation. Convergence was assessed to have been reached following the burn-in period, by examining

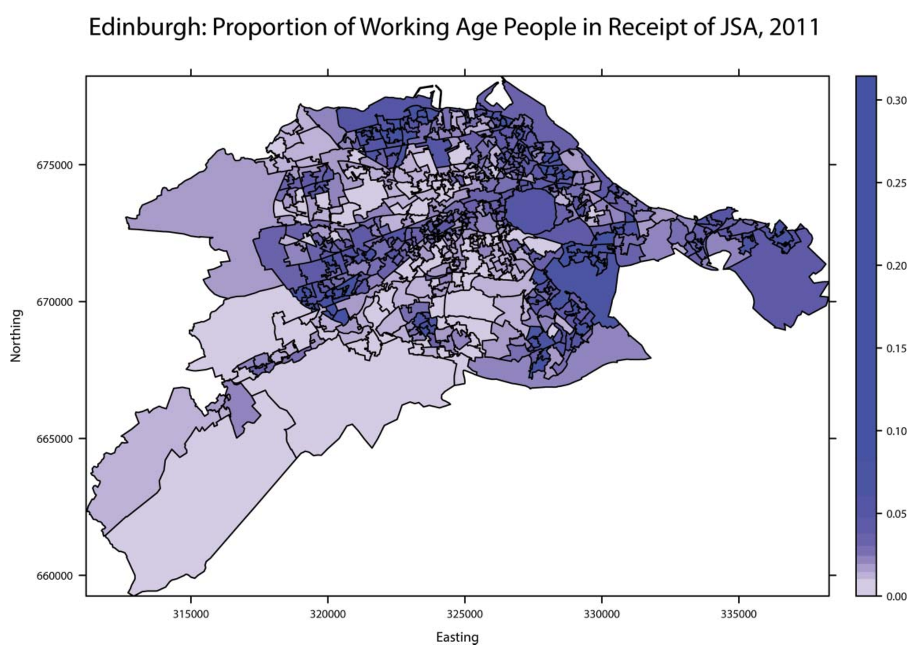

Figure 3. Proportion of people in receipt of job seekers allowance in 2011 in Edinburgh. JSA = job seekers allowance. (Color figure available online.)

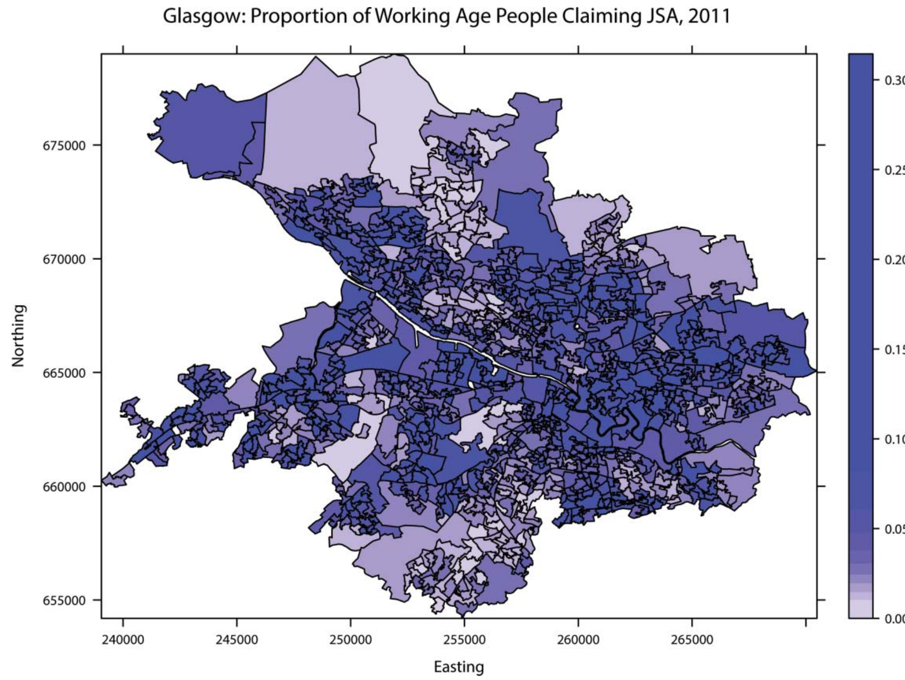

Figure 4. Proportion of people in receipt of job seekers allowance in 2011 in Glasgow. JSA = job seekers allowance. (Color figure available online.)

MCMC trace plots for sample parameters and by computing Geweke diagnostics (Geweke 1992). The key results presented in the remainder of this article concern the RCI and DI, so for brevity parameter estimates from the model are presented in the supplementary material accompanying this article.

Results: Global RCI

Computing the global RCIs required calculating the distance from the city center to the population weighted centroid of every data zone in the city. The estimated global RCIs and 95 percent credible intervals for each city, year, and benefit are presented in Table 1, where in each case the center of the city is defined by the location of its city hall. A sensitivity analysis to the definition of the city center is presented in the supplementary material accompanying this article. The supplementary material also contains a second sensitivity analysis with respect to how we have defined the geographical extent of each city.

Table 1 shows a number of key messages. First, the results are relatively robust to the choice of benefit, because the same substantive conclusions can be drawn regardless of whether IB, IS, or JSA are used in the analysis. Dundee and Glasgow show overwhelming evidence of the centralization of poverty in both years considered, with RCI estimates and 95 percent credible

Table 1. Relative centralization index (RCI) estimates and 95 percent credible interval for each city, year, and benefit

	Year	Aberdeen	Dundee	Edinburgh	Glasgow
IB	2001	0.065 (0.054, 0.077)	0.075 (0.065, 0.086)	−0.058 (−0.065, −0.050)	0.097 (0.093, 0.101)
	2011	0.003 (−0.011, 0.017)	0.021 (0.009, 0.034)	−0.095 (−0.104, −0.086)	0.040 (0.035, 0.045)
	Diff	−0.069 (−0.051, −0.087)	−0.055 (−0.038, −0.072)	−0.038 (−0.026, −0.050)	−0.057 (−0.050, −0.064)
IS	2001	0.056 (0.047, 0.066)	0.130 (0.121, 0.139)	−0.074 (−0.080, −0.068)	0.114 (0.111, 0.117)
	2011	0.008 (−0.006, 0.023)	0.036 (0.024, 0.048)	−0.129 (−0.139, −0.120)	0.044 (0.039, 0.049)
	Diff	−0.048 (−0.031, −0.065)	−0.094 (−0.079, −0.109)	−0.056 (−0.045, −0.067)	−0.070 (−0.064, −0.076)
JSA	2001	0.139 (0.119, 0.160)	0.132 (0.117, 0.146)	0.005 (−0.007, 0.019)	0.070 (0.062, 0.077)
	2011	0.089 (0.072, 0.106)	0.069 (0.055, 0.082)	−0.079 (−0.088, −0.068)	0.014 (0.008, 0.021)
	Diff	−0.059 (−0.032, −0.085)	−0.068 (−0.047, −0.089)	−0.088 (−0.072, −0.104)	−0.057 (−0.047, −0.067)

Note: The diff rows relate to the difference or change in RCI as RCI 2011 – RCI 2001. IB = incapacity benefit; IS = income support; JSA = job seekers allowance.

Table 2. Dissimilarity index estimates and 95 percent credible interval for each city, year, and benefit

	Year	Aberdeen	Dundee	Edinburgh	Glasgow
IB	2001	0.311 (0.303, 0.323)	0.253 (0.244, 0.262)	0.368 (0.361, 0.374)	0.317 (0.313, 0.320)
	2011	0.335 (0.325, 0.346)	0.273 (0.262, 0.284)	0.348 (0.341, 0.355)	0.309 (0.305, 0.313)
	Diff	0.024 (0.011, 0.038)	0.020 (0.006, 0.034)	−0.020 (−0.029, −0.011)	−0.008 (−0.013, −0.002)
IS	2001	0.367 (0.360, 0.374)	0.352 (0.345, 0.359)	0.426 (0.421, 0.431)	0.397(0.394, 0.399)
	2011	0.397 (0.385, 0.408)	0.349 (0.338, 0.359)	0.401 (0.394, 0.408)	0.358 (0.354, 0.362)
	Diff	0.030 (0.017, 0.043)	−0.004 (−0.016, 0.009)	−0.025 (−0.033, −0.017)	−0.039 (−0.043, −0.034)
JSA	2001	0.284 (0.268, 0.301)	0.281 (0.270, 0.293)	0.295 (0.284, 0.304)	0.256 (0.251, 0.262)
	2011	0.335 (0.320, 0.349)	0.283 (0.271, 0.294)	0.284 (0.276, 0.292)	0.279 (0.274, 0.284)
	Diff	0.050 (0.029, 0.072)	0.002 (−0.015, 0.017)	−0.010 (−0.023, 0.003)	0.023 (0.016, 0.030)

Note: The diff rows relate to the difference or change in RCI as RCI 2011 – RCI 2001. IB = incapacity benefit; IS = income support; JSA = job seekers allowance.

intervals being wholly positive. In both cases, however, poverty appears to have decentralized between 2001 and 2011, because the difference in RCI between the two years is wholly negative (RCI in 2011 – RCI in 2001) as measured by both its point estimate and 95 percent credible interval. In Edinburgh we find that almost all RCI estimates (except for JSA in 2001) and credible intervals are less than zero, suggesting that overall poverty was decentralized here even at the start of the study period. The difference in RCI between 2011 and 2001 is still negative, however, suggesting that further decentralization of poverty has taken place. Finally, Aberdeen shows evidence of a centralization of poverty in 2001 under all three benefits, but this has reduced in 2011 where it is not statistically significantly different from randomness for IB and IS.

Having addressed the first two key questions of interest (how centralized is urban poverty and to what extent is it decentralizing) we now turn to the question of whether it is becoming more spatially dispersed. We explore this in two ways, first using the traditional DI and then the local RCI measure.

Results for Dissimilarity Index

We estimated the DI as a measure of how evenly poverty is distributed across data zones in each of the four cities. The DI "measures the departure from evenness by taking the weighted mean absolute deviation of every [data zone's] minority proportion [those in poverty] from the city's overall minority proportion, and expressing this quantity as a proportion of its theoretical maximum" (Massey and Denton 1988, 284). Varying between zero and one, it tells us the proportion of poor households that would have to change data zone to achieve an even distribution, so the higher the value, the more uneven the distribution. The results (Table 2) suggest that there has been a statistically significant rise in DI by all three measures of poverty (IB, IS, JSA) in Aberdeen, which suggests that poverty has become less evenly dispersed across data zones. For Dundee, there was no significant change for two of the poverty measures. There were mixed results also for Glasgow, with JSA claimants becoming less evenly dispersed across data zones (increase in the DI) but with IB and IS claimants becoming more evenly distributed (fall in the DI). For Edinburgh, however, the DI fell for all three poverty measures. This suggests that in Edinburgh, poverty has become not only more decentralized but slightly more evenly dispersed.

The drawback of the DI is that it is essentially aspatial, so we turn now to assessing the local nature of centralization by computing the RCI locally for each aerial unit as suggested by Folch and Rey (2016). For a given data zone, the RCI is computed using the population-weighted centroids of each data zone, and for brevity these results are displayed in Figures 2S to 5S in the supplementary material accompanying this article. We interpret the local RCI as providing a measure of the spatial ordering of poverty (relative to nonpoverty) across the entire city around the neighborhood in question. If the RCI is strongly positive for a neighborhood, it suggests that there is clear spatial ordering of poverty around that neighborhood. As such, the neighborhood can be thought of as a "hub" for the spatial distribution of poverty, with rates of poverty in surrounding neighborhoods declining in concentric circles around the hub. So, it is possible that poverty has become less evenly spread across data zones (rise in the DI) but with the unevenness less obviously focused around particular hubs (a fall in the typical local RCI). This was the case for Aberdeen, for example. Local centralization of poverty also fell in Dundee and Glasgow. The local RCI also allows us to monitor shifts in the geographical locus of poverty. In Aberdeen, for example, we see a clear westward shift in the locus of poverty.

Edinburgh stood out from the other cities in the sense that poverty had very little spatial ordering around particular hubs, with many local RCI values close to zero in 2001. By 2011, however, local RCI values had become significantly negative on average. If the local RCI is negative it means that nonpoor households are located closer to a particular loci than poor ones. By 2011, a much stronger pattern of spatial ordering of data zones had emerged in Edinburgh, not around hubs of poverty but around hubs of nonpoverty. Those hubs for the spatial distribution of nonpoverty are more clearly bunched near the center by 2011, which corroborates the increased negativity of the global RCI for Edinburgh.

Summary and Future Directions

This article has focused on three primary questions: (1) How centralized is urban poverty? (2) To what extent is it decentralizing? (3) Is it becoming more spatially dispersed? With respect to the first two of these, we have argued that global centralization indexes still have a potentially important role in clarifying essential patterns in the decentralization of poverty. With respect to the third question, we have shown that local centralization indexes can provide a useful complement to dissimilarity indexes by revealing changes to the degree of spatial ordering around particular poverty hubs.

Crucially, however, we have attempted to address the important issue of inference that has been much over looked in relation to all three questions. To monitor and understand changes to twenty-first-century urban poverty we need a robust way to quantify uncertainty inherent in data that is partly a product of random population churn and characterized by spatial autocorrelation. We have proposed a method for computing robust statistical inference that can be applied to autocorrelated data and can estimate both levels of and change in global RCIs, local RCIs, and DIs. We hope that these methods will provide new levels of rigor for the international literature on the spatial distribution of poverty. Note that our novel approach to inference for the RCI and DI can equally be applied to other variables such as ethnicity, race, gender, social class, educational achievement, and so on.

In terms of avenues for future research, the statistically significant decentralization of poverty we have identified in all four cities raises a series of interesting and potentially pressing questions. What are the centripetal forces pushing poverty outward? To what extent is decentralization of poverty a knock-on effect of the Great Recession—suburban white-collar workers hit hardest as Scottish banks were severely weakened by the credit crunch? What is the role of ongoing and pervasive processes of gentrification—low-income households forced out of the city center by rising inner-city rents? Have changes in the allocation of public housing affected shifts across cities? Are there age- and sex-specific effects? What about changes to the system of welfare and pension provision—have these had an effect on the pattern of poverty? Both gentrification and white-collar unemployment are potentially exacerbated or mitigated by changes in welfare eligibility and provision.

These are questions that cannot be answered using the data employed here, because they require modeling individual decisions in a longitudinal context but are important and topical nonetheless. There is also the question of how sensitive our results would be to other measures of poverty. The three measures used here have produced consistent results, but there might be other ways of gauging poverty that we have not considered or that might not have been available in our study areas.

Finally, there are a broader set of questions to be explored regarding the implications for policy. How can we provide services to support the most vulnerable households in cities like Edinburgh if those households are becoming less centralized, more dispersed, and potentially less visible? Will these changing patterns of urban policy challenge our understanding of neighborhood effects and their policy implications? For example, does the decentralization of poverty, and the unravelling of extant spatial ordering of poverty with respect to traditional hubs of deprivation, undermine established social networks? If so, how will this affect behavior, life choices, and well-being? There is also the important question of how these spatial changes affect the likelihood of vulnerable households slipping through the welfare safety net and the impact on the incidence of unclaimed benefits. This might have implications for how we interpret the benefits data used in our study.

Understanding what has caused the change, what the impact is, and what the optimal policy interventions might be offers rich veins for exploration in the years ahead.

Acknowledgments

The authors gratefully acknowledge the helpful comments made by unnamed referees. The data were

accessed from the Scottish Neighbourhood Statistics Web site.

Funding

This work was funded by the Economic and Social Research Council (ESRC) through the Applied Quantitative Methods Network: Phase II, Grant Number ES/K006460/1.

Supplemental Material

Supplemental data for this article can be accessed on the publisher's Website at: http://dx.doi.org/10.1080/24694452.2016.1213156

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