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ARTICLE

Is the spatial persistence of deprivation dependent on neighbouring areas?

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Abstract

In the context of poverty and deprivation alleviation by national and local government, we use census data to explore 50 year trajectories of area deprivation to provide insight into how the spatial context of a community influences these trajectories. Using the temporal and spatial framework of spatial Markov models, we provide evidence for England and Wales on whether changing levels of deprivation over time are conditioned by areas having different types of neighbour. We find that, independent of the nature of their neighbours, there is high persistence of Most Deprived communities remaining deprived. Moreover, after conditioning by the type of neighbour, there is little likelihood of a Most Deprived neighbourhood improving when its neighbours are also the Most Deprived. However, Most Deprived neighbourhoods with Less Deprived neighbours have a greater likelihood of improvement. Communities that are the Least Deprived and have neighbours that are mostly Least Deprived, most likely remain Least Deprived. In terms of policy implications, targeting Most Deprived areas that have mostly Least Deprived neighbours can be considered 'quick wins'. It will also be resource efficient to target spatial clusters of Most Deprived communities rather than a similar number of isolated Most Deprived communities. This raises ethical questions around investing in some Most Deprived areas, but not in other, potentially more deprived, communities.

KEYWORDS

2021 Census, deprivation, England and Wales, neighbours, Spatial Markov models, trajectories

1 | INTRODUCTION

The study of the determinants and locations of communities that experience poverty and deprivation is long established, with such studies starting to become 'fashionable' in the Victorian era (Martin, 2008). This insight has been used through the decades to try and alleviate this poverty and improve the life experience for communities. One such mechanism is

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through government funding, with Ogden et al. (2023) finding that areas with higher socioeconomic deprivation tend to receive more funding for public services, between 10% and 15% more than the national average. Most recently, the UK government attempted to offset the loss of European Union regional Structural Funds with domestic initiatives, but these have not often been effective or well targeted (Nurse & Sykes, 2023) The importance of such targeting is highlighted by the finding that health outcomes (Dearden et al., 2020), social problems (Congdon, 2020) and general vulnerability to shocks (Hincks, 2017) can be exacerbated by the presence of deprivation. As well as government funding, other dynamics can affect the level of deprivation through changes in the mix of housing (Crook et al., 2016), population churn (Doan & Yudono, 2022) and employment (Lloyd, 2022).

While deprivation is experienced in the here and now, there are increasingly studies in the literature that assert it is important to consider the trajectories of deprivation (beyond the 'now') and the spatial context of deprivation (beyond the 'here'). A number of studies have characterised trajectories of deprivation, using an official measure of multiple deprivation (IMD) (Hincks, 2015; Houlden et al., 2024; Hughes & Lupton, 2021; Ministry of Housing Communities and Local Government, 2019); or more longer term trajectories using census-based estimates (Lloyd et al., 2023; Norman et al., 2024). Such studies have been able to identify types of communities where deprivation is particularly persistent, with typographies such as: 'entrenched disadvantage', 'persistently deprived' and 'isolates'. Hincks (2017) explores the complex pathways (260 in total) that deprived communities can take over just a 10 year timespan by examining various transition states.

An equivalent strand of work examines the spatial concentration of deprivation. Studies can be based on either a census geography (typically lower super output areas [LSOA]; Office for National Statistics, 2024a; Rae, 2009, 2012) or from a gridded representation of the population (Dearden et al., 2020; Lloyd, 2022; Lloyd et al., 2017). The degree of spatial correlation is typically measured using Moran's I statistic (Moran, 1950) or by local spatial autocorrelation (LISA) (Anselin, 1995). Here typologies exist that typify communities as exhibiting 'enclosed deprivation' or 'entrenched quarters of misery'. By taking each year of deprivation data as a cross-section and recalculating the indicators, a measure of how this concentration is changing over time can be derived.

This article explores these trajectories of deprivation and provides new insight into how the spatial context of a community conditions these trajectories, using the temporal and spatial framework of spatial Markov models. To determine whether deprivation trickles down (over time) and spills over (in space), we examine these research questions:

RQ1: To what extent and how quickly have communities changed their deprivation level?
RQ2: To what extent are these experiences conditioned by having different types of neighbour?
RQ3: What are the implications of these findings on how future policies may be implemented, in order to lift communities out of deprivation?

Intrinsic in these questions is what constitutes a (cohesive) community, in particular the scale and the assets which a community should possess. If the spatial extent is too small there is a risk that a number of isolated 'noisy' areas may be identified as deprived, which would not in themselves justify the resources to improve. If the spatial extent is too large, then a degree of smoothing may occur and 'pockets' of deprivation may be lost when aggregated with less deprived areas. Galster (2001, p. 2112) adopts a definition that a community consists of a '... bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses', and in Hincks (2015) lists certain criteria that a community could be expected to meet. We adopt some of the criteria listed in Hincks (2015), Guise and Webb (2017), and from the 15-minute neighbourhood concept (Mott MacDonald, 2022), and say that cohesive communities should possess most of these assets: employment opportunities; a variety of shops; a medical facility (pharmacy/dentists/GP); a financial asset (bank/Post Office/ATM); local school; a place of worship; access to parks/green space/blue space; a pub/club/café; and finally, public transport provision.

For our analysis there are two reasonable options for a definition of a community, either LSOAs or middle super output areas (MSOAs). Looking at figure 2.7.2 of Guise and Webb (2017), the geographic scale for the amenities listed above is at the intersection of neighbourhoods/urban districts, measuring an accessibility distance of around 1 km, and in urban and sub-urban areas this is more on the scale of MSOAs than LSOAs. Also by our calculations, the population and number of households within a 1 km walking buffer of a sample of English and Welsh unit postcodes is closer to that of MSOAs than LSOAs. Within these buffers, the median population is 7832 people and 3369 households, and the MSOAs' median population is 7957 people and 3303 households (the median number of people in an LSOA is much lower at 1605 and the median number of households is also lower, 665). For this study we have used the MSOA as the definition for our community.

The next section introduces the methods and data for this study. The following section provides the results, and the article finishes with a discussion of our findings.

2 | DATA AND METHODS

In this study, the measure of deprivation is the Townsend index constructed by Norman et al. (2024), covering the decennial censuses from 1971 to 2021 in England and Wales based on the 2021 Census MSOA geography. In the 50 year timespan of this series, the UK experienced a variety of economic conditions, with periods of economic prosperity but also various shocks: high oil prices in the 1970s; numerous recessions in the 1980s; post 2008 Great Recession austerity; the 2016 BREXIT vote; and the global COVID-19 pandemic in 2020/21 (see Fingleton et al., 2023; Figure 1).

The Townsend index relates to 'material' deprivation; a 'lack of goods, services, resources, amenities and physical environment which are customary, or at least widely approved in the society under consideration' (Townsend et al., 1988, p. 36) with four census-based indicators used: percentages of unemployment, car ownership, home ownership and household overcrowding. Apart from the unemployment variable, these inputs are not without their critics (Norman et al., 2024, p. 1202), but the variable definitions are closely equivalent over time such that changes in levels of deprivation can be captured. Since we are adopting an MSOA geography as our definition of a cohesive community, Norman et al. (2024) provided us with a bespoke Townsend index based on the larger geography of MSOAs.

Norman et al. (2024) also provided the population weighted pooled ranks for each 2021 MSOA in each census year, which have been converted into ordered quintiles and given the labels 'Most Deprived'; 'More Deprived', 'Medium Deprived', 'Less Deprived' and 'Least Deprived'. The use of this pooled ranking of deprivation scores, as opposed to cross-sectional ranks, aligns with the concept of 'Structural mobility or growth mobility' described in Rey (2015). The use of quintiles or deciles for this discretisation is commonly used in deprivation studies, with Wolf and Rey (2016) showing that for regional income data in the United States, the lumping into quartiles is sufficient to preserve first-order Markov behaviour and other desirable properties.

We use a spatial Markov model (Rey, 2001), which calculates the probabilities that communities transition between various quintiles of deprivation. The Markov assumptions are that the probability of changing from one deprivation category to another from time t to time $t+1$ relies solely on the deprivation category at time t (although with spatial Markov this changes slightly since the probability also relies on the deprivation category of the neighbours) and that the probabilities are time invariant. The model also provides the steady state of the system, which theoretically is the state that the process converges to and hereafter the distributions will no longer change, and is represented as the proportion of communities that rest in each quintile. The first mean passage time between quintiles is the mean time taken to move from one state to another or to return to the original state, where the return can be from any other state. The nuance of the spatial Markov model is that these calculations can be conditioned on the nature of the neighbours, under the assumption of the presence of a spatial lag effect (Rey et al., 2016). Thus the likelihood of communities to change their deprivation state is contingent on both their own deprivation state and that of their neighbours.

The spatial Markov model was implemented using the giddy package in Python (Kang et al., 2024) using the supplied deprivation quintiles, and a first order Queen contiguity spatial weights matrix for the MSOA (December 2021) boundaries (England and Wales) (Office for National Statistics, 2024b) calculated by the GeoDa software (Anselin et al., 2009). Where there are ties for the most common category of deprivation quintile for neighbours, the ties are broken using random draws, so the probabilities, steady states and mean first passage times here are calculated as the mean of 2500 random runs.

3 | RESULTS

In these results a comparison is made between the calculations when there is no conditioning on the category of neighbours ('Independent') and those when the neighbours are categorised as mostly 'Most Deprived'; 'More Deprived'; 'Medium Deprived'; 'Less Deprived' and 'Least Deprived'.

3.1 | Transition probabilities

This is the probability that a community will change from one category of deprivation to another over the 10 years between censuses. Figure 1 shows these probabilities, firstly when the probabilities are independent of the deprivation category of the neighbours (Figure 1a) and then when each of the neighbours are mostly of a particular deprivation category (Figure 1b–f).

(a) Independent	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.864	0.132	0.003	0.001	0.000
More Deprived	0.147	0.673	0.173	0.007	0.001
Medium Deprived	0.006	0.184	0.601	0.197	0.012
Less Deprived	0.001	0.013	0.203	0.578	0.205
Least Deprived	0.000	0.003	0.022	0.208	0.766

(b) Most Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.916	0.082	0.002	0.001	0.000
More Deprived	0.249	0.655	0.089	0.007	0.000
Medium Deprived	0.022	0.270	0.580	0.120	0.007
Less Deprived	0.016	0.046	0.260	0.570	0.108
Least Deprived	0.000	0.000	0.048	0.389	0.563

(c) More Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.721	0.272	0.005	0.000	0.001
More Deprived	0.151	0.682	0.161	0.004	0.001
Medium Deprived	0.009	0.228	0.608	0.146	0.009
Less Deprived	0.005	0.017	0.252	0.573	0.153
Least Deprived	0.003	0.003	0.028	0.224	0.742

(d) Medium Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.701	0.296	0.002	0.001	0.000
More Deprived	0.104	0.676	0.211	0.008	0.001
Medium Deprived	0.004	0.182	0.612	0.191	0.011
Less Deprived	0.002	0.014	0.234	0.576	0.175
Least Deprived	0.000	0.002	0.025	0.275	0.699

(e) Less Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.639	0.335	0.019	0.003	0.005
More Deprived	0.100	0.654	0.236	0.006	0.003
Medium Deprived	0.005	0.144	0.576	0.259	0.017
Less Deprived	0.000	0.012	0.193	0.585	0.209
Least Deprived	0.000	0.003	0.027	0.221	0.749

(f) Least Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	0.682	0.297	0.019	0.001	0.000
More Deprived	0.086	0.673	0.226	0.013	0.002
Medium Deprived	0.006	0.168	0.605	0.205	0.016
Less Deprived	0.000	0.011	0.180	0.570	0.238
Least Deprived	0.000	0.004	0.019	0.193	0.784

FIGURE 1 Transition probabilities: (a) independent of neighbours deprivation category; (b) neighbours mostly Most Deprived; (c) neighbours mostly More Deprived; (d) neighbours mostly Medium Deprived; (e) neighbours mostly Less Deprived; (f) neighbours mostly Least Deprived.

Steady State	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Independent	24.5%	21.8%	19.5%	17.7%	16.6%
Most Deprived	67.1%	21.8%	7.0%	3.3%	0.9%
More Deprived	19.9%	34.8%	23.6%	13.0%	8.7%
Medium Deprived	9.4%	25.6%	28.4%	22.5%	14.1%
Less Deprived	4.8%	15.9%	24.0%	29.2%	26.2%
Least Deprived	5.4%	17.9%	23.1%	24.6%	29.0%

FIGURE 2 Steady states.

As would be expected, in Figure 1a there are high values along the main diagonals; communities tend to be in the same deprivation category between censuses. The greatest inertia is seen in the Most Deprived communities, with a probability of 0.864 of remaining Most Deprived. As the probabilities move away from this main diagonal they decrease. There are very few communities that move between the 'extremes' over the 10 years between censuses. By examining Figure 1b–f we see that the inertia for the Most Deprived communities with mostly More Deprived neighbours has increased to 0.916 (Figure 1b), however this inertia reduces as the deprivation of the neighbours decreases, so that for such Most Deprived communities with Least Deprived neighbours it is just 0.682 (Figure 1f).

3.2 | Steady state percentages

The steady state of the system is shown in Figure 2. Without conditioning on the deprivation category of neighbours the proportion of communities in each deprivation category is around 20%, but not exactly 20% since pooled population weighted deciles are used. Looking at the remaining rows of this table, it is most likely that areas with neighbours of a particular deprivation category will also be in that category. For communities where the neighbours are mostly Most Deprived, 67.1% are Most Deprived; 7.0% are Medium Deprived and just 0.9% are Least Deprived. For communities that have mostly Least Deprived neighbours, 5.4% are Most Deprived but 29.0% are Least Deprived.

3.3 | Mean first passage time

Figure 3 shows the mean first passage time calculations and it is perhaps this that shows the starkest contrasts. Independent of its neighbours, a Most Deprived community will return back, having left this state, to being Most Deprived after 40 years, but it would take nearly 500 years to move to become Least Deprived (Figure 3a). When these times are conditioned by the deprivation category of most of its neighbours, this extends to 3.5 millennia (the ability of such communities to overcome their neighbourhood context to this degree is very, very unlikely) (Figure 3b). In fact, any community of any category surrounded by the Most Deprived will take millennia to move to or return to the Least Deprived deprivation quintile. The situation becomes less extreme for communities that have neighbours that are not Most Deprived (Figure 3c–f).

4 | DISCUSSION

Other studies have shown that the trajectory (Houlden et al., 2024; Lloyd et al., 2023; Norman et al., 2024) and spatial (Congdon, 2020; Crook et al., 2016; Rae, 2009, 2012) context of communities has an impact on their longer term experience of deprivation. Here we have used the spatial Markov framework to examine the effect of space on historic trajectories. Having conducted this analysis, we return to our research questions:

RQ1: To what extent and how quickly have communities changed their deprivation level? Independent of the nature of their neighbours, we see a high persistence for Most Deprived communities to remain deprived, with a less than 15% likelihood of reducing their deprivation. At the other end of the spectrum there is also some persistence, with the

(a) Independent	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	40.8	77.9	187.4	324.9	505.5
More Deprived	221.4	46.0	116.9	255.7	436.7
Medium Deprived	343.2	133.2	51.4	149.8	331.9
Less Deprived	410.9	202.1	87.5	56.6	198.5
Least Deprived	444.0	235.4	122.7	60.8	60.2

(b) Most Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	15	121	507	1238	3582
More Deprived	57	46	398	1134	3478
Medium Deprived	99	58	144	822	3155
Less Deprived	126	90	116	308	2444
Least Deprived	146	110	126	113	1113

(c) More Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	50	38	127	316	665
More Deprived	142	29	93	283	634
Medium Deprived	210	76	42	199	552
Less Deprived	254	124	63	77	383
Least Deprived	284	155	96	67	115

(d) Medium Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	106	35	97	194	375
More Deprived	321	39	64	162	342
Medium Deprived	424	113	35	105	286
Less Deprived	475	166	64	45	194
Least Deprived	503	194	92	43	71

(e) Less deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	210	44	81	138	228
More Deprived	540	63	55	114	207
Medium Deprived	717	196	42	66	160
Less Deprived	784	262	83	34	105
Least Deprived	813	291	114	48	38

(f) Least Deprived	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived
Most Deprived	187	43	86	162	254
More Deprived	547	56	58	134	226
Medium Deprived	697	170	43	87	180
Less Deprived	780	254	101	41	105
Least Deprived	814	289	138	56	34

FIGURE 3 Mean first passage times (years): (a) independent of neighbours deprivation category; (b) neighbours mostly Most Deprived; (c) neighbours mostly More Deprived; (d) neighbours mostly Medium Deprived; (e) neighbours mostly Less Deprived; (f) neighbours mostly Least Deprived.

Least Deprived communities with a less than 25% likelihood that their situation worsens. Higher levels of deprivation are more persistent than lower levels.

RQ2: To what extent are these experiences conditioned by having different types of neighbour? These experiences are greatly influenced by the type of neighbour. While Most Deprived communities struggle to improve, this struggle is exacerbated to a much greater extent when its neighbours are also the Most Deprived, reducing the probability of moving to a less deprived category from 15% to 8%. Communities that are the Least Deprived and have neighbours that are mostly Least Deprived have a high probability of remaining Least Deprived.

RQ3: What are the implications of these findings on how future policies may be implemented, in order to lift communities out of deprivation? This leads to a number of financially and ethically challenging alternatives:

a. Don't just 'treat' communities in isolation, it is easier to improve an area if all the neighbours are improved.
b. Abandon clusters of deprived communities because there is too much work to do.
c. Concentrate on the 'quick wins' that are deprived communities with less deprived neighbours.

To explore this, it is insightful to see how many communities fall into a combination of their own deprivation and that of their neighbours. Table 1 shows a count of these for 2021, with there being 1059 Most Deprived communities that have mostly Most Deprived neighbours and 26 that have mostly Least Deprived neighbours. Figure 2 shows that communities mostly surrounded by Least Deprived neighbours are more likely to be Least Deprived themselves, therefore these 26 communities that are currently Most Deprived, but have mostly Least Deprived neighbours, could be considered 'quick wins'. Alternatively, investing in the 1059 Most Deprived communities with Most Deprived neighbours may not achieve much; the existence of these neighbouring Most Deprived neighbours will constitute a challenge. Given the importance of this neighbourhood context, it would be more efficient to treat spatial clusters of the Most Deprived communities (even if in aggregate they are not the most deprived) rather than a similar number of isolated Most Deprived communities with mostly Most Deprived neighbours.

Mechanisms to influence these dynamics are varied and can operate on different time scales. Residential churn is perhaps the quickest mechanism, with a process of gentrification helping to lift communities out of deprivation, especially if they are located near to more sought after neighbourhoods (Yee & Dennett, 2022). For the medium term, governments may also implement policies aimed at reducing inequalities in society. Section 3.4 of Norman et al. (2022) looks at a range of socio-economic and socio-demographic attributes that are present in different types of deprivation trajectories. However, few of these are actually malleable by policy without some form of social engineering. Longer term dynamics are also influenced by the transfer of inter-generational wealth (or poverty) (Longley et al., 2021). Changes are also possible through improvements in the physical environment, and these can be expedited by external funding. Where these future funding resources are limited, it is illustrated here that it is perhaps better to spend them in locations where there is the greatest potential for improvement.

4.1 | Limitations

In this analysis, there exists two forms of edge effects. The first is administrative in nature and is a result of English MSOAs along the English and Scottish border not taking account of the nature of the deprivation in Scottish equivalents along the border. The second is a geographic effect and is particularly relevant for coastal locations. These locations, having the sea as a significant boundary, will have fewer neighbouring MSOAs than an inland location. Thus these MSOAs will be particularly sensitive to the nature of the deprivation for the few MSOAs that are their neighbours.

4.2 | Alternative analysis

Rather than adopting a pooled 'Structural mobility' perspective, it is reasonable to take a cross-sectional or 'Exchange mobility' (Rey, 2015) perspective. This relates to the question that Buck (2001, p. 2542) poses, 'does it make my life chances worse if my neighbour is poor rather than rich or a large proportion of my neighbours are poor, or disadvantaged on some other dimension?'. With this alternative perspective, the spatial Markov calculations can be easily recalculated

TABLE 1 Count of communities with a deprivation category and their neighbours in 2021.

	Neighbours					
2021 Census community	Most Deprived	More Deprived	Medium Deprived	Less Deprived	Least Deprived	Total
Most Deprived	1059	163	64	39	26	1351
More Deprived	196	668	260	176	148	1448
Medium Deprived	64	253	573	326	286	1502
Less Deprived	29	148	250	674	394	1495
Least Deprived	2	56	126	277	1007	1468
Total	1350	1288	1273	1492	1861	7264

using alternative quintile ranks. Another issue with the use of quintile ranks is that they may to a degree mitigate the effects for extremely deprived communities, say those in the most deprived decile. This can be examined by reworking the analysis with decile rather than quintile ranks, in which case there would be ten, 10 by 10 tables in each figure.

Alterative spatial weigh matrices may also be appropriate for different circumstances. Like Rae (2009) and Lloyd (2022), we have used first order Queen contiguity, but if the influence of communities further afield is thought to be important, then higher order contiguity could be used, or weight matrices based on identifying the N closest neighbours or those within a set distance threshold. These alternatives may be appropriate if some equivalence is required between the situation in urban (with a density of geographically small neighbours), sub-urban and rural locations (with a sparsity of geographically large neighbours).

The values provided in Figures 1–3 are estimates based on a consideration of the whole of England and Wales. It would be possible to do separate calculations for regions or sub-regions within England and Wales. Separate versions of Figures 1–3 are thereby possible, for example, for London and for Wales, allowing for different deprivation dynamics to be estimated for each region.

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CONFLICT OF INTEREST STATEMENT

The authors have no relevant financial or non-financial interests to disclose.

DATA AVAILABILITY STATEMENT

The data used in this study are available from the web sites and authors referenced in the article. The authors do not have re-distribution rights for these data. The code used for the study is available from the authors on request.

ETHICS STATEMENT

The data used in this study are open, non-personal data.

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