Modelling Local Spatial Poverty Traps in England

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Abstract

Spatial patterns of deprivation and segregation have changed little in England over the last twenty to thirty years, although there is anecdotal evidence of change over much longer periods of time. In this paper, a model is constructed and estimated that is consistent with short-run stability, but long-run change, based on thresholds and poverty traps. The model is consistent with the literature on social interactions, although this is not the only possible interpretation of the results. One of the implications of the model is that the same policies are not appropriate to all local areas. Using, as an example, an area targeted by the government for special measures – Harpurhey in Manchester – the paper demonstrates the difficulty of bringing the most deprived areas to take-off points where they can be self-sustaining. The paper argues that local areas rarely face changes of sufficient size to change their nature fundamentally. Therefore, the most deprived areas become stuck in poverty traps. Nevertheless, over the long term, areas undergo major periodic shocks capable of changing their status. But these changes are infrequent. Tracing one London street over the centuries, it is suggested that the main changes come from wars, natural disasters or major technological innovations, rather than from government policies.
1. Introduction

In this paper, some of the processes that contribute to poverty traps, in local areas, are discussed and modelled. Durlauf (2006, p143) suggests that, formally, poverty traps are limiting cases of economic immobility or are states in which the persistence of economic conditions is arbitrarily long. Bowles et al (2006) point to three strands of recent research that attempt to explain spatial poverty persistence; first, critical thresholds in wealth or human capital formation that have to be reached before countries or individuals can “take off”; second, unsuitable economic, social or political institutions that may trap countries in poverty. Engerman and Sokoloff (2006), for example, compare the historical development of countries in the Americas and argue that different initial inequalities in the distribution of resources affected subsequent institutional development and, indeed, current patterns of deprivation. Third, neighbourhood effects; under this general heading is a variety of social interactions and peer group influences. But the basic idea is that an individual’s behaviour depends not only on his or her own characteristics, but also on the position within a peer group. The role of peer group effects has been discussed in quantitative models of criminal behaviour and schooling, for example (Glaeser et al 1996). In such models, an individual’s educational performance depends not only on likely future returns to education, but also on the attitude towards education of the peer group. Poor performance by adolescent males is sometimes attributed to this source. The interactions lead to social multipliers, cumulative causation, increasing returns and poverty traps, since initial small shocks are reinforced through peer group interactions.

Neighbourhood effects (if they exist) potentially provide an attractive theoretical and quantitative framework for analysing the aggregate occurrences that we observe in local markets, since they may be able to explain why localised areas fail to thrive even if national economies are growing strongly. It is on this aspect of the poverty traps literature that the paper concentrates. However, it may be contrasted with an alternative approach to poverty traps, which considers intergenerational persistence, i.e. the extent to which the performance of children is determined by the economic status of the parents. In the UK, Long (2005) finds a high degree of intergenerational persistence in the 19th century and the evidence suggests that this has continued to the current time (Blanden et al 2006). Although a variety of transmission mechanisms are possible, one view is that parental income and education determine child health, for example, birth weight. Furthermore, there is evidence that low birth weights are related to subsequent educational attainment (see Currie and Hyson 1989, Black et al 2005). If intergenerational persistence dominates over neighbourhood influences, then spatial poverty traps are simply the locations where the poorly educated are forced to live. But the explanations are not mutually exclusive and, in principle, both can be nested in the same model.

The recent English government State of the English Cities report (ODPM 2006) appears to recognise some of the key issues:

“Cities are complex, self-organising market driven systems of economic, social, technological and social relationships. They differ in their economic, social and institutional structures. Each is the product of a unique history of development. These differences persist over time, so there are strong

\[1\] In the terminology of Manski (1993), intergenerational persistence provides exogenous contextual effects.
tendencies making for ‘path dependence’ in the patterns of size, function, and specialisation among cities. There are corresponding differences between cities in their capacity to adapt to changing technological, economic and market conditions and opportunities.” (page 66).

“… our evolutionary approach to the analysis of city economies has emphasised the significance of their long-term historical trajectories. They have arrived where they are today as a result of the long-term interactions between their particular circumstances and the external forces that have impacted on them. This approach shows not only that history matters, but that it takes a long time to develop along a particular path. It also shows that policy-makers and policies need similar long-term perspectives to achieve changes in those paths. There are no quick fixes that will turn around lagging city economies.” (p108)

The key words in the quotations are self-organisation, history, persistence, path dependence, external forces. In fact, the State of the Cities report does not attempt to derive an analytical framework that incorporates these concepts, but this paper begins to move in the direction. Although the empirical models are tested using modern data, they are set in a framework that is consistent with persistence and recognises the importance of history. Because spatial structures evolve only slowly, a long-run perspective is required (here from the 19th century). The models also emphasise the importance of various external forces that may tip areas into different states, including escapes from poverty traps. The paper argues that patterns of deprivation and segregation can be stable for lengthy periods, but over much longer periods, areas face different forms of shocks that change their nature. However, shocks of sufficient size to tip areas into a different state only occur infrequently. For similar reasons, standard government policy responses are rarely of sufficient magnitude for areas to escape poverty traps.

Models of social interactions can be tested in different ways. The observation of aggregate patterns of segregation, for example, may be prima facie evidence of poverty traps, although micro models in which poverty traps emerge as outcomes might be considered more elegant. In this paper, the models are tested on aggregate local data. A related strand of our work is constructing fully-estimated micro econometric models, but, arguably, prior analysis should concentrate on testing whether poverty traps exist at all in local areas – this is certainly of policy interest. Evidence for the existence of thresholds is particularly important, since thresholds may imply poverty traps and are consistent with the social interactions literature. Nevertheless, aggregate tests need to be treated with considerable caution and this is an econometric minefield. Such tests can rarely be conclusive, but it is possible to build up a portfolio of evidence, which is consistent with the existence of thresholds.

Section 2 presents initial evidence on the existence of segregation in England. Section 3 considers why thresholds arise and their consequences for poverty traps and segregation. Section 4 derives a joint model of local housing markets and deprivation and discusses the underlying econometric problems. The model is estimated in Section 5 and its properties are examined. In Section 6, the policy implications of the model are highlighted using two case studies of deprived areas; the first, Harpurhey in Manchester is receiving special government support. The model demonstrates the difficulties of turning the area around by conventional government measures. Therefore, the second case study looks at how areas do change and, given the quotations above, takes a long-run perspective, examining a small street in London called Saffron Hill. The street has experienced a variety of shocks over the last 150 years that have changed its status. Conclusions are drawn in Section 7.
2. Segregation, Deprivation and Policy in England

In January 2005, the Office of the Deputy Prime Minister\(^2\) unveiled its Five-Year Plan for neighbourhood revitalisation. Key objectives included:

“Faster progress to narrow the gap between the best and worst off to make sure opportunity and choice are for all, including a new more radical approach to renewal in a small number of very disadvantaged areas with the aim to create neighbourhoods with a more sustainable mix of tenures and incomes and address the problems of worklessness, skills, crime, poor environments and poor health.”

There are, clearly, a large number of possible indicators of mixed communities. The traditional concern of the US literature has been with \textit{ethnic} segregation. In the USA, Cutler \textit{et al} (1999) trace racial segregation in major cities from the late nineteenth century, based on census figures. But, in Britain, census questions on ethnicity have only recently been introduced. However, ethnic patterns are unlikely to be as concentrated as in the US. In London, the borough of Tower Hamlets has the highest concentration of Asian residents, comprising 36.6% of the total in 2001. But Ealing contains 14 Super Output Areas (SOAs) where the percentage is greater than 70%. Lambeth has the highest proportion of Black residents at 25.8%, but neighbouring Southwark contains 12 SOAs with Black percentages greater than 50%. Using data from the 1991 and 2001 censuses on the proportion of residents born abroad, Kyambi (2005), found that 7.5% of the overall English population fell into this group. In London, the proportion is 25% and the most concentrated local area is Wembley at 52%. Following the London bomb attacks in July 2005, issues of ethnic segregation and ghettos have risen sharply up the policy agenda. However, the emphasis here is on \textit{economic} rather than \textit{ethnic} segregation. Of course, the two are not unrelated and 70% of all English ethnic minority residents live within the country’s 88 most deprived districts (Neighbourhood Renewal Unit 2002). Hardman and Ioannides (2004) note the concentration of the US literature on racial segregation to the relative neglect economic segregation, and theirs is one of the few US studies of income segregation at fine, neighbourhood scales.

But, even limiting the study to economic segregation, the choice of indicators is potentially wide. In a comprehensive study of the spatial distribution of poverty in Britain, Green (1994) compares the positions in the 1981 and 1991 censuses, using the unemployment rate, the percentage of households with no car, tenure, inactivity rates, occupational class and qualifications\(^3\). In this section, we concentrate mainly on unemployment, although Meen \textit{et al} (2005) extend the analysis to a wider set of variables. Furthermore, although segregation is a multi-dimensional concept (Massey and Denton 1988), the paper uses the most common measure of segregation in the literature, i.e. the Index of Dissimilarity, in order to aid comparisons with earlier work.

Figure 1 presents this unemployment-based Dissimilarity Index for the English local authority districts (LAD) in 2001, calculated across almost 8,000 wards. The most segregated

\(^2\) The English housing ministry.

\(^3\) Note that the list does not include income, which is not available from the UK census. At a very fine neighbourhood level (using individual households as kernels), Hardman and Ioannides (2004) find, in the US, that there is more mixing than might be expected, although some poor neighbourhoods are still highly income segregated. However, their work illustrates one of the problems of using income data. Observed low or high incomes in any time period may represent temporary shocks, overstating the true degree of income integration. Measures based on education may be a better indicator of permanent income.
districts are labelled. Overall, eleven of the fifteen top ranked local authorities lie in the North of the country (North East, North West, Yorkshire and Humberside) and none in the South East. But, for policy, the question is whether these rankings and, indeed, the absolute levels of the indices have changed over time. The second question is more difficult to answer since the exact definitions of the ward boundaries over which the LAD indices are constructed have altered over time. Nevertheless, patterns can still be discerned in the scores and rankings. Green found a broad pattern for 1991. She found that, in England, Middlesbrough (3), Stockton (2), Preston (4), and West Lancashire (6) were the districts of highest segregation – again all lying in the Northern part of England. The numbers in brackets are the rankings in 2001. Therefore, the most highly segregated local authorities in 1991 remain high on the 2001 list. In 1991, Middlesbrough yielded a dissimilarity score of 0.31, similar to the 2001 value, despite the ward boundary changes. Furthermore, in terms of changes between 1981 and 1991, Green points to a high degree of continuity in the spatial distributions. The evidence from Dissimilarity Indices, therefore, points to the stability of segregation patterns between 1981 and 2001, at least on the unemployment indicator, with the most segregated communities existing in large, older industrial areas. Dorling and Rees (2003) reach similar conclusions. Comparing the four censuses since 1971, they, in fact, conclude that polarisation has increased, although their analysis uses local authorities (rather than wards), which makes standardisation across censuses slightly easier.

In summary, the key result is that patterns of segregation appear to change little over 20-30 year periods, despite the thrust of policy, although the paper demonstrates later that, over much longer periods, they may undergo major structural changes.

![Figure 1. Index of Dissimilarity – Unemployment Based](image-url)
3. Thresholds, Poverty Traps and Segregation

The segregation of wealthy households from the poor is predicted by a number of strands of urban economic theory, even if discrimination or physical controls are ignored. But not all of the theories imply thresholds, nor rely on social interactions to achieve their results. In fact, it appears that government policy for mixed communities is fighting against strong market trends.

First, the standard monocentric model implies that spatial distributions depend on the income elasticity of housing demand relative to the income elasticity of the marginal valuation of commuting time (Muth and Goodman 1989). If the former is large relative to the latter, high income groups are more likely to be concentrated in the suburbs than in the inner city. However, Wheaton (1977) suggests that the two elasticities are similar in size, in which case mixing becomes more likely. Second, Evans (1976), demonstrates how segregation is more likely to occur when household preferences are interdependent.

Third, recent work by Bayer et al constructs models on micro data for the San Francisco area (2004) and on aggregate census tract data across the US (2004a). The models highlight the role that a shortage of neighbourhoods for well-educated, black households plays in patterns of segregation and integration. The authors suggest that the current shortage promotes a degree of integration since well-educated black households have to choose between living with low-income black households or well-educated white households (given a preference for living amongst households of similar characteristics). However, as the percentage of well-educated black households increases over time, this is likely to raise segregation since more neighbourhoods for high-income black households become available.

Fourth, a series of papers by Galster and his collaborators (Quercia and Galster, 1997, Galster and Zobel, 1998, Galster et al, 2000, Galster, 2002, Galster 2003) investigates the evidence for thresholds in considerable detail. Although he generally finds the empirical evidence to be mixed, he points to three behavioural mechanisms, which may generate non-linear, threshold-like outcomes – collective socialisation, contagion and gaming. The importance of these effects depend on the extent to which individuals come into contact with a peer group and the extent to which the group can exert influence or impose threats on the individual. The group has to reach a critical mass before it exerts influence on the behaviour of others.

Fifth, a similar set of conclusions arise from the literature on self-organising cities, using techniques from complexity theory. This strand is a development of the classic Schelling (1971) model, whose central insight is to demonstrate that, even if all agents wish to live in mixed (integrated) neighbourhoods, the sum of the individual free choices will, typically, generate segregated communities. Further extensions to a stochastic world by Young (1998) demonstrate that segregation is a stochastically stable state. Although an accumulation of shocks may eventually tip the world into a different state, exhibiting thresholds, patterns of segregation are likely to be long-lasting. Models of this form often use cellular automata to demonstrate the key properties.

In summary, contagion models and models following the Schelling tradition typically exhibit tipping points, thresholds or phases of transition, consistent with the generation of poverty traps. Neighbourhoods do not start to decline or gentrify until they pass some trigger point, but past the threshold, their status changes quickly. Therefore, the approaches provide a
framework for analysing some of the aggregate occurrences that we observe in local housing markets, including cumulative decline, low demand areas, and the loss of city populations. Furthermore, it provides a framework in which patterns can be stable for long periods of time, but eventually change as areas pass the threshold.

As an illustration, in Figure 2 (based on Galster and Zobel 1998), the level of neighbourhood poverty is shown on the horizontal axis, expressed as a deviation from the mean. Therefore, positive values indicate higher than average levels. The vertical axis captures some indicator of social or economic conditions, for example income, here scaled to a maximum value of unity. If the relationship between poverty and income is linear, we would expect to observe the broken line in Figure 2. But if peer group pressures and contagion are important (for example affecting the willingness to work or propensity to commit crime), then local income might not take off until poverty falls to a critical point (B).

![Figure 2. Thresholds in Local Housing Markets](image)

The areas that are most likely to gentrify or decline are those that lie around the thresholds, but the identification of these areas is critical. Appropriate policy intervention is also tied up with identifying the thresholds. Relatively small government expenditures (or other forms of exogenous or endogenous shocks) in areas that lie around points (A) and (B) have large effects on incomes. By contrast, expenditure at locations well above (B) may have very little effect. In other words, “one size fits all” policies do not work where thresholds exist. Threshold models exhibit poverty traps, but linear models do not. In practice, in the next two sections, local house prices rather than local incomes are used as the variable on the vertical axis since data on local incomes are typically of lower quality than local house prices. Since there is a large literature that shows house prices are strongly (log) linearly related to incomes, at least at the national and regional levels (see, for example, Meen 1999, Meen 2002), the model in Figure 2 also implies a non-linear relationship between house prices and poverty – a trap in terms of local housing markets.

Models of this type also have implications for the economic efficiency (rather than distributional equity) of schemes, such as Moving to Opportunity (MTO), designed to move
low-income households away from poorer areas. Galster (2002) shows that if the relationship
between neighbourhood incomes and the poverty rate in Figure 2 is linear, there are no
efficiency gains (measured in terms of net social benefits) from shifting populations. This
arises because the gains to poor households who move to richer areas are offset by the losses
to rich households who already lived in those areas. On efficiency grounds, it is insufficient
to demonstrate that the incomes of the poor rise on moving. For any gains to occur, the
relationship has to be non-linear.

4. An Aggregate Analysis of Poverty Traps

Galster (2003) proposes the structure of a simultaneous model to explain home ownership,
mobility, neighbourhood character, housing wealth and socio-economic status, capable of
being estimated on longitudinal databases for individuals or households, although Galster
does not actually estimate the model. Furthermore, in Galster and Zobel (1998), he stresses
the dangers associated with simple cross-section hedonic house price studies that find a
negative relationship between individual house prices and the proportion of poor in any
neighbourhood, because of the difficulties in distinguishing causation. Macro structural
weaknesses in an area, unrelated to the current level of poverty, may reduce house prices and
allow poor households to move into the area. Therefore, high levels of deprivation might
equally be caused by low house prices. The literature on social interactions stresses the value
of experimental approaches, but the UK has no equivalent of the Moving to Opportunity
programme, sometimes used as an experimental base in the US. In this and the following
section we suggest that a portfolio of evidence in support of non-linearity can be compiled on
aggregate data, although no single diagnostic test can be convincing. If we find that linearity
holds, this suggests that interactions are unimportant, but we have to be cautious in
concluding the reverse and that thresholds exist. Furthermore, aggregate data are not
sufficiently rich to conclude that any non-linearity arises from neighbourhood or peer group
influences, although the results may be consistent with such an interpretation. There are a
large number of difficult econometric issues to be taken into account, associated with the
identification and endogeneity issues raised by Manski (1993) and Moffitt (2001). The model
that is put forward here does not cover all the variables suggested by Galster, but is a joint
model of the two key variables - local house prices and deprivation.

Four classes of variable that affect the location choices of individual households may be
identified, (i) the characteristics of the households themselves, both demographic and
economic, (ii) features of the neighbourhood, for example local amenities, (iii) the combined
characteristics of the current inhabitants of each neighbourhood, which include the presence
of peer groups, and (iv) the characteristics of other (nearby) locations, which generate spatial
spillovers. For the moment, we ignore the last of these (but return to the question briefly
later). Using the approach in Haurin et al (2003), the following (owner-occupier) housing
demand function for household \((i)\) in each location\(^4\) can be specified:

\[ H_i = x_i \beta + \Pi_i^{\delta} \theta + \bar{x}_i^{\gamma} \gamma + z_i^{\delta} \delta + \epsilon_i \]

\(^4\) The spatial subscript is suppressed for convenience.
where:

\[ \begin{align*}
H_i &= \text{owner-occupier housing demand by household (i) in each neighbourhood} \\
x_i &= \text{a vector of individual characteristics of (i), both economic and demographic} \\
\bar{H}_N &= \text{the average owner-occupation rate in each neighbourhood} \\
\bar{x}_N &= \text{the average characteristics of individuals in each neighbourhood} \\
z_N &= \text{a vector of physical characteristics in each neighbourhood (including amenities and the price of housing)} \\
\varepsilon_i &= \text{error term}
\end{align*} \]

The equation includes three interaction terms. The first represents the average owner-occupancy rate and the second average neighbourhood population characteristics, e.g. income, both of which are endogenous. The third represents contextual effects, which, with the exception of price, are exogenous. If the coefficients are the same across individuals, then pooling of the data is possible, but in the reduced form of (1), the coefficients on the group effects are not separately identified. Furthermore, equation (1) suffers from a correlated unobservables problem. Since, in practice, the \( x_i \) are unlikely to be able to capture the full-range of relevant characteristics, any correlation between the unobservables, captured in the error term, and the neighbourhood indicators is likely to overstate the influence of the latter. For example, parental income or parental labour market status is unobservable in many samples and, potentially, persistence models indicate that this could be correlated with the neighbourhood indicators. Although instrumentation of the neighbourhood indicators potentially provides a solution, in practice, finding valid instruments is not straightforward since, in many instances, the chosen instruments will still be correlated with the error term.

Equation (2) defines the average individual characteristics of the neighbourhood, whereas (3) gives the average owner-occupation rate (assuming the mean error is zero).

\[
\bar{x}_N = \frac{1}{I_N} \sum x_i
\]

(2)

\[
\bar{H}_N = \frac{1}{I_N} \sum x_i \beta + \bar{H}_N \theta + \bar{x}_N \gamma + z_N \delta
\]

(3)

or

\[
\bar{H}_N = \bar{x}_N \beta + \bar{H}_N \theta + \bar{x}_N \gamma + z_N \delta
\]

(4)

or

\[
\bar{H}_N = \bar{x}_N \frac{(\beta + \gamma)}{(1 - \theta)} + z_N \frac{\delta}{(1 - \theta)}
\]

(5)

Solving out (3) gives equation (5), the aggregate owner-occupation demand in each area, which is now related to the average characteristics of individuals in the neighbourhood and

\[ ^5 \text{An alternative approach, where panel data sets exist, is to remove individual fixed effects, i.e. unobservable variables, by differencing over the time periods. In the results in Section 5, although data for two time periods are available, this approach cannot be adopted because of changes in the definitions of the variables over time.} \]
the characteristics of the area itself. Since one of the area characteristics will be price ($P^N$), the vector $z^N$ may be partitioned into $[z^{1N} | P^N]$, giving (6).

$$H^{dn} = \bar{x}^N \frac{(\beta + \gamma)}{(1-\theta)} + z^{1N} \frac{\delta_1}{(1-\theta)} + P^N \frac{\delta_2}{(1-\theta)}$$ (6)

If the housing stock $\bar{H}^{SN}$ is fixed in each area in the short run, the short-run price equation for each neighbourhood is given by equation (7).

$$P^N = -\frac{(1-\theta)}{\delta_2} \bar{H}^{SN} + \bar{x}^N \frac{(\beta + \gamma)}{(\delta_2)} + z^{1N} \frac{\delta_1}{\delta_2}$$ (7)

But equation (7) shows that there are five parameters with only three estimated coefficients. Therefore, the equation highlights the identification problem; in terms of this equation alone, it is not possible to distinguish the separate influence of the neighbourhood characteristics from the average characteristics of the individuals. However, below, the two are combined in a single indicator and, for the issue of non-linearity, this is not too much of a problem in this case.

Returning to the influence of spatial spillovers, the demand for housing in any area is likely to depend also on the characteristics (including price) in neighbouring areas. One approach is to employ techniques taken from the spatial econometrics literature. If $W$ is a spatial weights matrix, then the general price equation becomes (8), where $z^{2N}$ is a vector of characteristics in other neighbourhoods and the final term represents spatial spillovers.

$$P^N = -\frac{(1-\theta)}{\delta_2} \bar{H}^{SN} + \bar{x}^N \frac{(\beta + \gamma)}{(\delta_2)} + z^{1N} \frac{\delta_1}{\delta_2} + Wz^{2N} \frac{\delta_4}{\delta_2}$$ (8)

A number of other specification issues and problems need to be considered. First, equation (8) is linear – the neighbourhood variables have a proportionate effect on prices, whatever their levels. But, from Figure 2, if local income is non-linearly related to poverty, inclusion of the latter as a regressor in (8) generates a testable non-linearity.

Second, in addition to individual fixed effects, equation (8) ignores spatial fixed effects, which may be correlated with the included regressors and, therefore, lead to biased coefficients. Consequently, each variable is measured relative to the regional mean in an attempt to remove region-wide influences. This spatial differencing is the equivalent of time differencing used to remove individual fixed effects. For example, the model, estimated on local authority data, uses the deviation of local authority deprivation from the regional average as one of the regressors. Since deprivation is generally higher in the North than in the South East, the approach takes out some of the region-wide structural economic influences that are approximately constant within regions. This allows us to consider local variation in conditions, standardising on regional or national influences. This only provides a partial solution since there are structural economic differences within regions – for example Manchester and Liverpool are parts of different Travel to Work Areas within the North West region, and experience different economic conditions.
Third, since (8) includes no lags, issues of causality and endogeneity arise. As noted earlier, on cross-section data, a finding of a negative relationship between house prices and poverty cannot, by itself, be taken as evidence of causality – low house prices might equally cause high levels of poverty as low income households are attracted to those areas. However, there is sufficient lagged information to provide some indication of causality. In addition, a joint simultaneous model of local prices and deprivation is estimated by FIML to account for possible endogeneity. Furthermore, lagged values of deprivation, for example, provide valid instruments in the model of local house prices since there is no correlation between the contemporaneous error term and lagged deprivation.

Fourth, problems arise because, at local authority level, a limited range of deprivation values is observed. Most local authorities have “good” and “bad” neighbourhoods, which average out over the local authority as a whole. Therefore, capturing effects at the tails (our main interest) is difficult and there are dangers of extrapolating outside observed experience. A battery of diagnostic tests is applied to overcome the problem, including stability tests and tests of functional form.

Finally, an important conceptual problem arises, which affects estimation and implies that typical time-series data cannot be used to test the hypotheses. By definition, if poverty traps exist, in any one area, we would not expect tipping to occur frequently. On typical time-series data sets of say 20-30 years, an area is likely to remain within one state. The cellular automata models in Meen and Meen (2003), for example, and the long-run historical analysis undertaken later both suggest that tipping takes place rarely. Therefore on time-series data for one area, the probability of observing a non-linear function in the data is very low, even if a threshold model is the true representation. We would simply observe a linear segment of the threshold model. Therefore, the long-run time-series model has to be approximated by a cross-section spatial model. Local authority data (354 observations) are employed. Again, since the model emphasises that local spatial structure changes only very slowly, because of poverty traps, the observations at one point of time are likely to be a reasonable approximation of the (temporary) equilibrium between phase transitions. If the model is valid, then the use of cross section data is a reasonable approach (given the above caveats) to testing for poverty traps.

5. Estimation of the Joint Model

5.1 Model Specification

The S-Shaped (threshold) price function can be represented by a logistic function (9).

\[
y_i = 1 - \frac{b_1}{1 + e^{(c_2 + c_3 IMD_i + c_4 (H/HH)_i + c_5 (INC)_i + \epsilon_i)}}
\]  

\(y_i\) = local authority house prices relative to the maximum regional price in which the local authority exists

\(IMD\) = Index of Multiple Deprivation (relative to regional average)

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6 Empirical evidence not presented here suggests that small deviations away from the equilibrium are restored in subsequent time periods.
Equation (10) provides an alternative close approximation to the logistic function. In this case, linearity simply requires \( a_5 = a_6 = 0 \). For the moment, both equations exclude the spatial spillovers term from (8), so the variables in the equations need to be related to those in (7). The key variable is the measure of poverty (so that the equation represents Figure 2). The Index of Multiple Deprivation is employed as a composite indicator of the average characteristics of individuals in the area and of the average physical characteristics of each area. As noted above, it is not possible to identify separately the individual influences. But since we are primarily interested in testing non-linearity, aggregating the terms into a single indicator is not problematic. In fact, the Index of Multiple Deprivation is available for both 2000 and 2004 (but calculated by different methods), which helps to overcome the causality and endogeneity problems, since local house prices are available for the same periods. The Index ranks the level of deprivation in every English local authority area. It combines a number of indicators covering income, employment, health deprivation and disability, education skills and training, housing quality and geographical access to services into a single score for each area.

The remaining regressors are common to much of the house price modelling literature. Firstly, a supply-side measure of the owner-occupier housing stock is included, consistent with (7). Meen (2002) demonstrates the substantial omitted variable biases that arise from the omission of the housing stock in price equations. However, rather than simply the housing stock, a better measure is the owner-occupier housing stock per household. This preserves homogeneity – a doubling of the housing stock and the number of households has no effect on prices. The second variable added is a measure of local average household income, constructed by Wilcox (2003, 2005). Arguably, the effect of income is already partially captured in \( \text{IMD} \), but since income has consistently been found to be an important variable in house price studies, it is included as a separate regressor.

The English local authority districts are chosen as the unit of measurement. In principle, the model should be estimated at very fine spatial scales, since thresholds and tipping are neighbourhood phenomena. But formal models at finer spatial scales are heavily affected by noise, arising from small sample size and measurement problems for house prices. Some tests were conducted on ward level data, but, as expected, the noise is high and data on local incomes are not available at that scale.

The dependent variable \( (y_i) \) in both (9) and (10) is measured as the ratio of each local authority level price to the highest district price in the corresponding region. As discussed earlier, this reduces the influence of spatial fixed effects and the transformation ensures that the dependent variable is defined continuously over the range zero\(^7\) to unity, with the most

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\( H \) = number of owner-occupied dwellings (relative to regional average)

\( HH \) = number of households (relative to regional average)

\( INC \) = household income (relative to regional average)

\( \varepsilon \) = error term

\( i \) denotes a spatial subscript
expensive district in each region taking a value of unity. The independent variables are measured in terms of regional deviations.

The second equation in the joint model explains the deprivation index. Although the Index of Multiple Deprivation combines many indicators, in practice, it can be explained by a limited range of indicators available from the 2001 Census. Bailey and Pickering (2004) reach a similar conclusion for Scotland. The key variables are given in (11).

\[
IMD_i = b_0 + b_1 UR_i + b_2 AGE_i + b_3 NOQUAL_i + b_4 ILL_i + b_5 NW + b_6 y_i + \varepsilon_{3i} \tag{11}
\]

- \( UR \) = % of the population aged 16-74 who are unemployed
- \( AGE \) = % of the population aged 16-74 who are retired
- \( NOQUAL \) = % of the population aged 16-74 who have no qualifications
- \( ILL \) = % of the population with limiting long-term illness
- \( NW \) = % of the population who are Black or Asian

All variables are measured relative to regional averages.

Perhaps, contrary to expectations, the equation does not include any relationship between deprivation and tenure. It is undoubtedly true that areas of high deprivation are associated with heavy concentrations of social housing, but this does not necessarily imply that social housing causes deprivation. The appropriate causality tests are, however, difficult to conduct on cross-section data.

Notice that the equation is linear. The reason is that in the price equation, the predicted value from (11) is used as the regressor rather than the measured value\(^8\). By itself, this is unlikely to provide a valid instrument to overcome the omitted variables problem discussed above, since it is still likely to be correlated with the error term as the independent variables in the \( IMD \) equation may not be truly exogenous. Rather the estimated value is used because the official measure of \( IMD \) is a complex indicator and a value of 100, for example, does not mean an area is twice as deprived as one with 50. Therefore the variable used is an estimated linear combination of the variables that are found to be important in explaining \( IMD \). Therefore, it can be ranked properly in a way that the official measure cannot. Failure to do so, could artificially induce non-linearity into the price equation. The omitted variables problem is tackled instead by including lagged values of \( IMD \).

Equation (9) or (10) and (11) give the joint model to be estimated simultaneously later, although the next sub-section begins with single equation estimates. Both equations satisfy identification conditions.

### 5.2 Single Equation and Systems Estimates

Single equation estimates (using predicted values of \( IMD \)) of the logistic price equation (9) are presented in Table 1. Here data for 2001 are used throughout. The equation is estimated for England as a whole and for the meta regions of the South, North and the Midlands. Meen (1999) indicates that these meta regions minimise aggregation bias. In all cases the deprivation variables are highly significant with similar coefficients across the regions. The remaining coefficients are also significant with expected signs.

---

\(^8\) In these cases \( b_6 \) is set equal to zero.
Notice that the values of $b_1$ have been imposed. As noted above, this ensures that the value of the dependent variable lies between one and a non-zero minimum value, since the average price of housing never falls to zero. Usually $b_1=0.723$, which implies that the minimum local authority house price is 27.7% of the regional maximum.

Using the first row of Table 1, Figure 3 plots the estimated relationship between prices and deprivation (broken line), calculated at the means of the remaining variables and the function has the expected shape. However, deprivation in most local authority districts lie in the central part of the distribution and the assumed functional form may be artificially (and invalidly) imposing the shape of the relationship. Therefore a set of tests is required for non-linearity.\(^9\) Equation (10) forms the basis for the first set of tests and, as noted above, linearity simply requires zero coefficients on the power terms. The first four rows of Table 2 present the results from the simple linear model (at different spatial scales). The final row (for England) adds the powers. The quadratic term is statistically significant and the equation outperforms the equivalent linear model. Note also that the equation standard error and $R^2$ are similar to those in the corresponding equation in Table 1. This is expected because the quadratic function proves to be a good approximation to the logistic.

\textbf{Table 1. Parameter Estimates in the Logistic House Price Equation (2001 data)}

<table>
<thead>
<tr>
<th>Area</th>
<th>$b_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
<th>$R^2$</th>
<th>SEE</th>
<th>Obsn</th>
</tr>
</thead>
<tbody>
<tr>
<td>England (ex. London)</td>
<td>0.723</td>
<td>-0.307</td>
<td>-0.080</td>
<td>-0.034</td>
<td>7.38E-05</td>
<td>0.69</td>
<td>0.090</td>
<td>320</td>
</tr>
<tr>
<td></td>
<td>(imposed)</td>
<td>(8.9)</td>
<td>(13.4)</td>
<td>(5.3)</td>
<td>(8.7)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>0.711</td>
<td>-0.564</td>
<td>-0.094</td>
<td>-0.041</td>
<td>5.11E-05</td>
<td>0.72</td>
<td>0.087</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>(imposed)</td>
<td>(8.9)</td>
<td>(10.1)</td>
<td>(4.2)</td>
<td>(2.1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Midlands</td>
<td>0.723</td>
<td>-0.502</td>
<td>-0.101</td>
<td>-0.056</td>
<td>7.95E-05</td>
<td>0.81</td>
<td>0.071</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>(imposed)</td>
<td>(6.8)</td>
<td>(9.1)</td>
<td>(3.8)</td>
<td>(3.9)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>0.685</td>
<td>-0.267</td>
<td>-0.090</td>
<td>-0.023</td>
<td>6.68E-05</td>
<td>0.68</td>
<td>0.089</td>
<td>159</td>
</tr>
<tr>
<td></td>
<td>(imposed)</td>
<td>(5.3)</td>
<td>(7.8)</td>
<td>(2.5)</td>
<td>(5.6)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(t\)-values in brackets

North = North East, North West, Yorkshire & Humberside

Midlands = East Midland, West Midlands

South = East, South East, South West

SEE = equation standard error

\(^9\) In fact, for most of the policy results that follow, it is not strictly necessary for the threshold model to hold. The weaker requirement is that the relationship between prices and deprivation is not linear.
Table 2. Parameter Estimates in the Linear and Polynomial House Price Equations

<table>
<thead>
<tr>
<th>Area</th>
<th>Const</th>
<th>IMD</th>
<th>H/HH</th>
<th>INC</th>
<th>IMD²</th>
<th>IMD³</th>
<th>R²</th>
<th>SEE</th>
<th>Obsn</th>
</tr>
</thead>
<tbody>
<tr>
<td>England (ex.</td>
<td>0.595</td>
<td>-0.0116</td>
<td>-0.0048</td>
<td>1.14E-05</td>
<td>-</td>
<td>-</td>
<td>0.67</td>
<td>0.093</td>
<td>320</td>
</tr>
<tr>
<td>London)</td>
<td>(109.9)</td>
<td>(13.3)</td>
<td>(4.7)</td>
<td>(8.7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>0.566</td>
<td>-0.0136</td>
<td>-0.0062</td>
<td>8.03E-06</td>
<td>-</td>
<td>-</td>
<td>0.69</td>
<td>0.092</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>(54.2)</td>
<td>(9.3)</td>
<td>(3.3)</td>
<td>(2.6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Midlands</td>
<td>0.575</td>
<td>-0.0137</td>
<td>-0.0085</td>
<td>1.47E-05</td>
<td>-</td>
<td>-</td>
<td>0.78</td>
<td>0.076</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>(57.9)</td>
<td>(8.8)</td>
<td>(3.9)</td>
<td>(5.0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>0.622</td>
<td>-0.0110</td>
<td>-0.0026</td>
<td>1.07E-05</td>
<td>-</td>
<td>-</td>
<td>0.66</td>
<td>0.092</td>
<td>159</td>
</tr>
<tr>
<td></td>
<td>(81.3)</td>
<td>(7.3)</td>
<td>(1.9)</td>
<td>(6.1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>England (ex.</td>
<td>0.577</td>
<td>-0.0123</td>
<td>-0.0044</td>
<td>1.15E-05</td>
<td>0.0002</td>
<td>1.89E-06</td>
<td>0.69</td>
<td>0.091</td>
<td>320</td>
</tr>
<tr>
<td>London)</td>
<td>(84.8)</td>
<td>(9.7)</td>
<td>(4.3)</td>
<td>(8.9)</td>
<td>(3.8)</td>
<td>(0.4)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Further Tests of Linearity

<table>
<thead>
<tr>
<th>Area</th>
<th>Const</th>
<th>IMD</th>
<th>H/HH</th>
<th>INC</th>
<th>DA</th>
<th>DB</th>
<th>DD</th>
<th>DE</th>
<th>R²</th>
<th>SEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>England (ex.</td>
<td>0.576</td>
<td>-0.0160</td>
<td>-0.0042</td>
<td>1.16E-05</td>
<td>0.0005</td>
<td>0.003</td>
<td>0.006</td>
<td>0.0084</td>
<td>0.69</td>
<td>0.091</td>
</tr>
<tr>
<td>London)</td>
<td>(73.2)</td>
<td>(6.0)</td>
<td>(4.2)</td>
<td>(9.1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3. Relationship Between House Prices and Deprivation

Second, RESET tests for model specification can be employed. At the national level the linear, logistic and polynomial functions all exhibit heteroscedasticity. A RESET test for functional form yields a highly significant F-value of 10.9 for the polynomial form. But the misspecification arises from inappropriate spatial aggregation. The estimation of separate equations for the three main regional blocs removes heteroscedasticity and RESET tests are easily passed in all cases (insignificant F-values of 1.0, 1.8 and 0.7 for the North, Midlands and the South respectively)

The third test of functional form attempts to measure directly the slope of the curve at different levels of deprivation through spline functions. Therefore, five dummy variables (DA-DE) are defined for different ranges of deprivation. These are summarised below:
DA: IMD < -12.0 (n=30)
DB: -12.0 < IMD < -5.0 (n=77)
DC: -5.0 < IMD < +5.0 (n=145)
DD: 5.0 < IMD < 12.0 (n=62)
DE: IMD > 12.0 (n=39)

The test is similar to that used by Krivo and Peterson (1996) in their study of the effect of disadvantaged neighbourhoods on crime rates in Ohio. The disaggregation again emphasises the concentration of observations in the central ranges; 145 observations lie in the range ±5.0. Nevertheless, the ranges have been chosen so that significant numbers are in the tails of the distributions. The disadvantage of this approach is that the break points are arbitrary, although data driven. Equation (12) defines the equation to be estimated as an extension of the linear equation. The null hypothesis of linearity, therefore, requires \( a_5 = a_6 = a_7 = a_8 = 0 \).

\[
y_i = a_1 + a_2 \text{IMD}_i + a_3 (H/HH)_i + a_4 (INC)_i + a_5 DA_i \times \text{IMD}_i + a_6 DB_i \times \text{IMD}_i + a_7 DD_i \times \text{IMD}_i + a_8 DE_i \times \text{IMD}_i + \varepsilon_i
\]  

(12)

Since the dummies sum to unity, one dummy, \((DC)\), is omitted. Therefore the slope coefficients are measured relative to that in the central range. Table 3 indicates that, indeed, at high levels of deprivation, the dummy variables are significant.\(^{10}\) We expect the coefficients to be positive since \( a_2 \) is negative, in order to reduce the slope. In fact at very high levels of deprivation, the coefficients would be expected to be approximately equal and opposite in sign under the threshold hypothesis. In the sample, there are no extremes, but \( a_8 \) is still approximately half the size of \( a_2 \). In other words, when deprivation is greater than a value of 12.0, the effect of a change in deprivation on prices is a half of that when deprivation is in the range ±5.0. By contrast there appears to be less evidence of non-linearity in areas where deprivation is particularly low, since neither \( a_5 \) nor \( a_6 \) are significantly different from zero. But, to summarise, all the tests so far suggest that there is evidence of non-linear responses at high levels of deprivation.

The results could be biased by the failure to allow for spatial spillovers (equation 8). The extent to which local housing markets are linked is, of course, of interest in its own right. For example, if government expenditures are increased in one market, do they have spillover effects on neighbouring areas? But the interest here is in spatial interactions as a form of specification test. Since we are modelling areas based on administrative boundaries rather than true local housing market areas, spatial interactions are expected. But does a failure to take account of these interactions lead to a bias in the coefficients of models that omit the interactions as a form of omitted variable bias? For example, does the non-linearity of the model disappear once spatial interactions are taken into account?

Two forms of the model are tested – standard spatial error and lag models. The spatial weights matrix is based on first-order contiguity. Because of the nature of the weights matrix, estimation covers all the local authorities including London. The only district that has no spatial linkages is the Isle of Wight. Modelling takes place using Spacestat; however the

\(^{10}\) Notice that, again, the degree of fit is similar to the threshold equation in Table 1, suggesting that the choice of break points is reasonable, although the logistic function is more parsimonious.
package does not readily allow the estimation of logistic functions and, hence, the polynomial function is used from Table 2.

The first row of Table 4 repeats the final row of Table 2 for comparison purposes. The second row adds back London and excludes the insignificant cubic term. The results remain similar. The statistics below are the LM tests for spatial errors and lags and the Kelejian-Robinson test for spatial errors. The K-R test is the most appropriate where errors are non-normal, is applicable to linear and non-linear models and requires less information on the form of the weights matrix. In the presence of normally-distributed errors the two versions of the LM test can be used to discriminate between spatial lag and error models. All tests follow $\chi^2$ distributions with one degree of freedom.

<table>
<thead>
<tr>
<th>Test Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM (error)</td>
<td>157.0</td>
</tr>
<tr>
<td>LM (lag)</td>
<td>57.8</td>
</tr>
<tr>
<td>Kelejian-Robinson (error)</td>
<td>111.7</td>
</tr>
</tbody>
</table>

All tests strongly indicate some form of spatial dependence. Although there is some evidence that the spatial error model is the appropriate from the LM tests, both forms are estimated. The third row of Table 4 adds a spatial lag ($\rho$). The model is now estimated by FIML. The spatial lag coefficient is significant with a positive value of 0.329 and the overall fit of the equation improves. Nevertheless, the failure to take account of spatial lags has little effect on the remaining coefficients, which remain similar to the previous values. The non-linearity remains significant. The final row is the spatial error model ($\lambda$). This simply improves the efficiency of the earlier estimates, but failure to take into account spatial error correlation does not bias the OLS estimates. The spatial error coefficient is highly significant, but, as expected, there is little effect on the remaining parameters.

Table 4. Parameter Estimates Including Spatial Interactions

<table>
<thead>
<tr>
<th>Area</th>
<th>Constant</th>
<th>IMD</th>
<th>H/HH</th>
<th>INC</th>
<th>IMD$^2$</th>
<th>IMD$^3$</th>
<th>$\rho$</th>
<th>$\lambda$</th>
<th>R$^2$</th>
<th>SEE</th>
</tr>
</thead>
<tbody>
<tr>
<td>England (ex. London)</td>
<td>0.577</td>
<td>-0.0123</td>
<td>-0.0044</td>
<td>1.15E-05</td>
<td>0.0002</td>
<td>1.89E-06</td>
<td>-</td>
<td>-</td>
<td>0.69</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(84.8)</td>
<td>(9.7)</td>
<td>(4.3)</td>
<td>(8.9)</td>
<td>(3.8)</td>
<td>(0.4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>England</td>
<td>0.571</td>
<td>-0.0127</td>
<td>-0.0057</td>
<td>8.07E-06</td>
<td>0.0002</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.63</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>(81.4)</td>
<td>(14.7)</td>
<td>(6.3)</td>
<td>(8.7)</td>
<td>(3.5)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>England</td>
<td>0.330</td>
<td>-0.0107</td>
<td>-0.0042</td>
<td>7.593</td>
<td>0.0002</td>
<td>-</td>
<td>0.329</td>
<td>-</td>
<td>0.68</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(7.2)</td>
<td>(12.3)</td>
<td>(4.9)</td>
<td>(8.9)</td>
<td>(4.7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>England</td>
<td>0.562</td>
<td>-0.0134</td>
<td>-0.0060</td>
<td>7.779</td>
<td>0.0002</td>
<td>-</td>
<td>-</td>
<td>0.643</td>
<td>0.66</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>(45.7)</td>
<td>(16.5)</td>
<td>(7.5)</td>
<td>(9.4)</td>
<td>(5.7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

T-values in brackets

The difficulties of endogeneity and of disentangling causation in which all variables are current dated was raised above. Although we do not have time series, enabling us to conduct Granger causality tests, observations are available for both 2001 and 2004 and this

---

11 Although the published IMD relates to 2000 (rather than 2001), the use of predicted values, taking independent variables for 2001, means that the variables in the model are effectively all current dated.
information can be exploited. First, the national equation in Table 1 is re-estimated on 2004 data (first row of Table 5)

**Table 5. Parameter Estimates in the Logistic House Price Equation**  (2004 data)

<table>
<thead>
<tr>
<th>Area</th>
<th>$b_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
<th>$R^2$</th>
<th>SEE</th>
<th>Obsn</th>
</tr>
</thead>
<tbody>
<tr>
<td>England (ex. London) (imposed)</td>
<td>0.786</td>
<td>0.315</td>
<td>-0.094</td>
<td>-0.029</td>
<td>2.65E-05</td>
<td>0.61</td>
<td>0.096</td>
<td>320</td>
</tr>
<tr>
<td>England (ex. London) (imposed)</td>
<td>0.786</td>
<td>0.306</td>
<td>-0.071</td>
<td>-0.022</td>
<td>2.50E-05</td>
<td>0.61</td>
<td>0.097</td>
<td>320</td>
</tr>
</tbody>
</table>

t-values in brackets

The 2004 relationship between prices and deprivation is shown as the unbroken line in Figure 3. The curve is slightly steeper, but *IMD* remains highly significant. The main difference is the lower coefficient on income. However the income data are taken from Wilcox (2005) and are not entirely consistent with the earlier vintage. Therefore, the coefficients are not necessarily comparable. But, broadly, the equation remains similar on the later data set. In order to allow for endogeneity, one approach is to include the lagged 2000 Deprivation Index as a two step estimator in the 2004 price equation, since the 2004 errors are uncorrelated with the 2000 Index. The second row of Table 4 suggests that lagging the variable has little effect on the conclusions. The reverse test where lagged prices are used as a regressor in the *IMD* equation is set out below.

In anticipation of the results of the next section, the key result shown in Figure 3 is that the thresholds lie at approximate values of ± 30. Although not shown in the figure, the curve becomes almost completely flat at values of approximately ± 70. The main implication of the curve is that policy would have to reduce deprivation in any area to a value of approximately 30, before it will “take off” of its own accord. If regeneration expenditures only reduce deprivation from, say, 70 to 60, the impact is very modest. Consequently, since most areas typically do not experience large shocks regularly, it is unsurprising that spatial structures remain stable for long periods of time. Furthermore, arguably, the trick for both government and private investors is to identify those areas that lie just above the threshold, since modest expenditures generate large returns. Commenting on these findings, Beroube (2005) notes:

- The conventional wisdom is that any area can be regenerated given the right level of investment, but this misses the point. Indeed, it might be possible to reduce deprivation from 70 to 30, but the question is whether society has the resources to bring about the desired level of regeneration in all areas. As discussed below, the required resources can be very large indeed.
- “Incremental improvements in social conditions of the most severely deprived communities may produce little market response, and may thus fail to catalyse the broader forces on which regeneration programmes depend. Again these communities are not necessarily beyond “the point of no return”, but the effort needed to achieve sustainable improvements in those places, absent some more radical intervention, may exceed what society is willing to expend”. (Beroube, 2005, p. 29).
Table 6 provides details of the estimated equations for deprivation, using the 2000 Index (IMD). All independent variables are taken from the 2001 Census. The equations are estimated across all the English local authorities and disaggregated by region, but typically the same set of variables turns out to be important in all regions. But note, for the moment in these single equation versions, house prices are not included as a regressor.

In all cases, unemployment is a major influence. The incidence of long-term illness is also an important factor. An absence of qualifications has a more variable effect, but this is because of the high correlation between qualifications and unemployment. Ethnicity appears to be more important in the North of the country than the South in explaining deprivation. The first row of Table 7 repeats the national equation using the 2004 Index. However (in the absence of alternatives) all the independent variables remain 2001 values, taken from the Census; all variables are still significant and the fit, measured by the $R^2$ is high for a cross section.

The second row conducts the causality test, by adding lagged (2001) values of house prices to the equation. The addition of the variable has little effect on the remaining coefficients and is only borderline significant at the 5% level (t-value = 2.0). But the coefficient is positive and, therefore, cannot be consistent with the view that low house prices cause an inflow of low income migrants, raising the level of deprivation. For completeness, the final row adds the contemporaneous (2004) house price and the story remains the same.

**Table 6. Explaining Deprivation (Dependent variable = IMD 2000)**

<table>
<thead>
<tr>
<th>Region</th>
<th>Constant</th>
<th>UR</th>
<th>AGE</th>
<th>NOQUAL</th>
<th>ILL</th>
<th>NW</th>
</tr>
</thead>
<tbody>
<tr>
<td>England</td>
<td>1.860</td>
<td>4.290</td>
<td>-1.188</td>
<td>0.262</td>
<td>1.908</td>
<td>0.136</td>
</tr>
<tr>
<td>England (ex. London)</td>
<td>1.901</td>
<td>3.790</td>
<td>-1.234</td>
<td>0.265</td>
<td>1.992</td>
<td>0.100</td>
</tr>
<tr>
<td>North East</td>
<td>2.609</td>
<td>3.608</td>
<td>-0.270*</td>
<td>0.323*</td>
<td>2.062</td>
<td>1.370</td>
</tr>
<tr>
<td>North West</td>
<td>3.373</td>
<td>5.297</td>
<td>-1.601</td>
<td>0.161*</td>
<td>2.034</td>
<td>0.368</td>
</tr>
<tr>
<td>Yorks &amp; Humber</td>
<td>3.769</td>
<td>3.017</td>
<td>-1.205</td>
<td>0.454</td>
<td>1.781</td>
<td>0.352</td>
</tr>
<tr>
<td>E. Midlands</td>
<td>2.332</td>
<td>6.190</td>
<td>-0.371*</td>
<td>0.208*</td>
<td>1.272</td>
<td>1.143</td>
</tr>
<tr>
<td>W. Midlands</td>
<td>5.903</td>
<td>4.267</td>
<td>-0.818</td>
<td>0.113*</td>
<td>1.957</td>
<td>0.192*</td>
</tr>
<tr>
<td>East</td>
<td>0.457</td>
<td>4.511</td>
<td>-1.047</td>
<td>0.369</td>
<td>1.660</td>
<td>0.106*</td>
</tr>
<tr>
<td>Greater London</td>
<td>0.281</td>
<td>5.611</td>
<td>-2.080</td>
<td>0.871</td>
<td>0.634*</td>
<td>0.019*</td>
</tr>
<tr>
<td>S. East</td>
<td>0.733</td>
<td>3.451</td>
<td>-1.312</td>
<td>0.273</td>
<td>2.064</td>
<td>0.114</td>
</tr>
<tr>
<td>S. West</td>
<td>0.208</td>
<td>4.044</td>
<td>-0.928</td>
<td>0.272</td>
<td>2.029</td>
<td>0.336*</td>
</tr>
</tbody>
</table>

All variables are measured relative to regional averages
* denotes insignificantly different from zero at the 5% level.

**Table 7. Explaining Deprivation (Dependent variable = IMD 2004)**

<table>
<thead>
<tr>
<th>Region</th>
<th>Constant</th>
<th>UR</th>
<th>AGE</th>
<th>NOQUAL</th>
<th>ILL</th>
<th>NW</th>
<th>y</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>England</td>
<td>1.499</td>
<td>3.67</td>
<td>-1.142</td>
<td>0.111</td>
<td>1.596</td>
<td>0.052</td>
<td>-</td>
<td>0.90</td>
</tr>
<tr>
<td>England</td>
<td>0.032*</td>
<td>3.61</td>
<td>-1.206</td>
<td>0.166</td>
<td>1.652</td>
<td>0.049*</td>
<td>2.609</td>
<td>0.90</td>
</tr>
<tr>
<td>England</td>
<td>-0.398*</td>
<td>3.62</td>
<td>-1.231</td>
<td>0.172</td>
<td>1.650</td>
<td>0.047*</td>
<td>3.010</td>
<td>0.90</td>
</tr>
</tbody>
</table>

* denotes insignificantly different from zero at the 5% level.

12 Since IMD changes so slowly over time, the use of future values for the independent variables causes few problems.
Equations (10) and (11) can also be estimated as a system by FIML and results are given in Table 8. All the significant variables from the single equation estimates remain significant. Comparing the results with Table 2, the coefficients in the price equation are very similar and there is no evidence that the non-linearity is less. In the deprivation equation, the price term is again positive. Therefore, none of the conclusions above are changed by systems estimation.

In conclusion, there is strong evidence from a battery of diagnostic tests and estimating techniques to reject the linear relationship between local house prices and deprivation. Nevertheless, it is still necessary to be cautious in concluding that the threshold model is the valid data representation. Furthermore, on aggregate data, the econometric problems are such that we cannot necessarily conclude neighbourhood and peer group effects are the cause of any non-linearity. The best we can say is that the aggregate results are consistent with the literature on peer group and contagion effects. Therefore prima facie, there is evidence to support the carrying out of more detailed micro and experimental work.

Table 8. FIML Estimation of House Prices and Deprivation (England excluding London, 2001)

<table>
<thead>
<tr>
<th>Coefficient (yi)</th>
<th>Estimate (t-value)</th>
<th>Coefficient (IMDi)</th>
<th>Estimate (t-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$</td>
<td>0.581 (72.6)</td>
<td>$b_1$</td>
<td>3.637 (10.4)</td>
</tr>
<tr>
<td>$a_2$</td>
<td>-0.0138 (13.4)</td>
<td>$b_2$</td>
<td>-1.373 (11.5)</td>
</tr>
<tr>
<td>$a_3$</td>
<td>-0.0052 (4.5)</td>
<td>$b_3$</td>
<td>0.367 (6.2)</td>
</tr>
<tr>
<td>$a_4$</td>
<td>9.74E-0.06 (7.1)</td>
<td>$b_4$</td>
<td>2.047 (14.2)</td>
</tr>
<tr>
<td>$a_5$</td>
<td>0.00021 (3.6)</td>
<td>$b_5$</td>
<td>0.087 (2.5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$b_6$</td>
<td>3.397 (11.2)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.67</td>
<td></td>
<td>0.91</td>
</tr>
<tr>
<td>Standard error of regression</td>
<td>0.093</td>
<td></td>
<td>2.69</td>
</tr>
</tbody>
</table>

6. Escaping Poverty Traps

Escape from poverty traps requires the most deprived local areas to reach the take-off points. As discussed below, periodically, areas may experience large shocks that bring them to those points; wars, natural disasters or technological change are typically of such magnitude as to force radical change upon an area. But more modest policy changes may be insufficient for areas to reach the take-off point. The quotation from Beroube (2005) above suggests that the required government expenditures for the most deprived areas to reach the take-off point may be prohibitive. Consequently, areas become stuck in a poverty trap. But, whatever the source, major shocks typically have to occur in order to induce radical change. Since such shocks occur infrequently, stable patterns emerge and it may well take decades or even centuries to observe major change. To demonstrate these points, three analyses are conducted:

(i) A case study of Harpurhey in Manchester, in order to illustrate the difficulties for the most deprived areas in reaching the take-off point.
(ii) An examination of the proportion of small areas (COAs) in England stuck well above the threshold
(iii) A case study of a street in London, which is traced from the 19th century.

13 Variables found to be insignificant in Tables 2 and 7 are excluded.
In Figure 3, the thresholds lie at values of approximately ±30, but the curve becomes almost completely flat at values of approximately ±70. The values are an index, but to give a feel for the magnitudes involved, in the North West the maximum value of the index for a local authority district is 28 in Knowsley, (after subtracting the regional average value). Therefore, even the most deprived local authorities are only just around the threshold. In fact, most districts lie in the steepest part of the curve. The implication is that, no local authority can be “written off” as a whole – even the most deprived local authorities have their wealthy parts. Consequently, there is no policy ineffectiveness result at the local authority level. This is hardly surprising since most local authorities have a mixture of “good” and “bad” areas. This suggests the need to look at deprivation at a finer spatial level as in the following subsections.

6.1 Harpurhey – A Case Study

The UK government’s Five Year Plan for neighbourhood revitalisation includes targeting three estates - Harpurhey in Manchester, Gipton in Leeds and Canning Town in Newham. But it can be shown how difficult the process of regeneration will prove. Concentrating on Harpurhey (highlighted as the most disadvantaged neighbourhood in the country) Table 9 sets out the characteristics of the ward at the time of the Census.

Table 9. Summary Indicators for Harpurhey (2001)

<table>
<thead>
<tr>
<th>Harpurhey Ward</th>
<th>Manchester</th>
<th>England &amp; Wales</th>
</tr>
</thead>
<tbody>
<tr>
<td>% in employment</td>
<td>41.4</td>
<td>46.4</td>
</tr>
<tr>
<td>% unemployed</td>
<td>6.4</td>
<td>5.0</td>
</tr>
<tr>
<td>% limiting long-term illness</td>
<td>29.8</td>
<td>21.5</td>
</tr>
<tr>
<td>% with no qualifications</td>
<td>51.5</td>
<td>34.0</td>
</tr>
<tr>
<td>% with a degree</td>
<td>8.6</td>
<td>21.4</td>
</tr>
<tr>
<td>% in owner-occupation</td>
<td>33.6</td>
<td>41.8</td>
</tr>
<tr>
<td>% in social housing</td>
<td>52.4</td>
<td>39.4</td>
</tr>
</tbody>
</table>

Source: Census

Compared with both Manchester as a whole and England and Wales, Harpurhey has a very low percentage in employment, unemployment almost twice the national average, a poorly educated labour force, predominantly living in social housing. But the coefficients in Table 6 provide an indication of how far some of these variables would have to change in order to bring about a significant reduction in deprivation. The first row of the table implies that a one percentage point reduction in the unemployment rate would reduce deprivation by approximately 4.3 points. Therefore, in Harpurhey, for example, if unemployment fell to the Manchester average, deprivation would fall by approximately six points, keeping the other variables constant. Reducing those with long-term illness to the Manchester average might cut deprivation by approximately sixteen points. A similar reduction in those with no qualifications is estimated to reduce deprivation by 5 points. In practice, these factors are all inter-related and a package would affect all. A programme that managed to reduce all three elements to the Manchester average might cut deprivation, therefore, by 27 points. But since the value of the IMD in Harpurhey in 2001 was 78.28 (48 in terms of the deviation from the regional mean), the resource requirements needed to reduce the index to the take-off point of 30 are likely to be very large. Again this stresses the size of the necessary shock.

The reduction in deprivation, in principle, could occur either by immigration of the high skilled into the area or by an improvement in the skills of the indigenous labour force. However Meen et al (2005) show that turnover (both population inflows and outflows) are
low in the more deprived areas. High skilled migrants do not want to move to the most deprived areas, whereas the low skilled are stuck in them. Improving the skills of local residents is also not a quick fix. The Introduction noted the importance of intergenerational persistence. There is evidence, for example, that low income mothers have children with low birth weights and low birth weights are related to subsequent educational attainment (see Currie and Hyson 1989, Black et al 2005). Therefore, it may take generations to turn round an area by this route. It also raises a wide range of social policy issues, for example, the quality of child care provision or the relationship between housing quality and child health. Given these problems, which contribute to poverty traps, Section 6.3 below looks at how urban areas do, in fact, change their status.

6.2 The Proportion of Census Output Areas above the Deprivation Threshold

As noted above, there are no local authority districts that lie well above the threshold. This suggests the need to look at deprivation at a finer spatial level. In terms of the 2000 IMD, the next finest spatial scale in England is the ward level. Although details are not presented here, there are still few wards that have deprivation values (relative to the regional average) significantly greater than 50. Therefore, in most cases, the most deprived wards are beyond the threshold, but not dramatically so.

The 2004 Index gives results at the finer Super Output Area (SOA) level. Beroube (2005) gives the number and proportion of SOAs that lie above a level of 40. He defines these as “extremely deprived SOAs” and the results are reproduced as Table 10. Nationally, approximately 1.5% of SOAs fall into this category. But there is a wide dispersion with a heavy concentration on the North West. It should be remembered that this does not just represent a generally higher level of deprivation in the North West since each is expressed in terms of differences from regional averages.

Table 10. Extremely Deprived Neighbourhoods, 2004

<table>
<thead>
<tr>
<th>Region</th>
<th>Extremely Deprived SOAs (Nos.)</th>
<th>Extremely Deprived SOAs (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>East Midlands</td>
<td>55</td>
<td>2.0</td>
</tr>
<tr>
<td>East</td>
<td>17</td>
<td>0.5</td>
</tr>
<tr>
<td>London</td>
<td>14</td>
<td>0.3</td>
</tr>
<tr>
<td>North East</td>
<td>31</td>
<td>1.9</td>
</tr>
<tr>
<td>North West</td>
<td>190</td>
<td>4.3</td>
</tr>
<tr>
<td>South East</td>
<td>26</td>
<td>0.5</td>
</tr>
<tr>
<td>South West</td>
<td>31</td>
<td>1.0</td>
</tr>
<tr>
<td>West Midlands</td>
<td>53</td>
<td>1.5</td>
</tr>
<tr>
<td>Yorks &amp; Humberside</td>
<td>77</td>
<td>2.3</td>
</tr>
<tr>
<td><strong>England</strong></td>
<td><strong>494</strong></td>
<td><strong>1.5</strong></td>
</tr>
</tbody>
</table>

Source: Beroube (2005)

Further evidence can be obtained at the finer Census Output Area level. Although the IMD was not officially constructed at this scale, an approximation can be made using the equations in Table 6. Since the independent variables are available at COA level, estimates of the Deprivation Index can be obtained, using the coefficients in the table.

Dealing with COAs involves large amounts of data. Therefore we concentrate on four of the English regions – the North East (8,599 observations), North West (22,710), Yorkshire and Humberside (16,793) and the South East (26,646). These are chosen as the areas of highest
deprivation, to be contrasted with the region of lowest deprivation. The estimated distribution of deprivation at COA level in the North West is mapped in Figure 4 highlighting the main areas of poverty. In Knowsley, for example, the estimated maximum level of deprivation in any COA is a staggering 134\textsuperscript{14}. Maps of the remaining areas can be found in Meen et al (2005).

![Figure 4. Estimated Deprivation in the North West](image)

In Table 11, three summary measures are presented; (i) the proportion of Output Areas with estimated deprivation indices lying in the range ±30, i.e. those lying in the steepest part of the price curve; (ii) the proportion with values greater than 70, i.e. the flattest part of the curve; (iii) the standard deviation of scores. Here the interest is in whether the dispersion of outcomes is narrower in the wealthier South East than in the North.

<table>
<thead>
<tr>
<th>Region</th>
<th>Number of COAs</th>
<th>COAs lying between ±30 (%)</th>
<th>COAs lying above 70 (%)</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>North East</td>
<td>8,599</td>
<td>73.5</td>
<td>1.3</td>
<td>27.28</td>
</tr>
<tr>
<td>North West</td>
<td>22,710</td>
<td>77.5</td>
<td>1.2</td>
<td>26.18</td>
</tr>
<tr>
<td>Yorks &amp; Humber.</td>
<td>16,793</td>
<td>78.9</td>
<td>1.2</td>
<td>25.62</td>
</tr>
<tr>
<td>South East</td>
<td>26,646</td>
<td>91.6</td>
<td>0.4</td>
<td>18.18</td>
</tr>
</tbody>
</table>

Clearly, the vast majority of COAs lie within the steepest part of the price curve. This is true in all regions and particularly in the South East. Remember, the higher value for the South East does not represent the generally lower level of deprivation in the South, since all calculations are relative to regional means. Most COAs are therefore amenable to policy action. But there are important tails – and these are precisely the areas most typically targeted

\textsuperscript{14} But care must be expressed at COA level. These have an average population size of approximately 200. Therefore, small numbers of the unemployed, for example, finding jobs have a large impact on the calculated index value.
for action. In the North, slightly more than 1% of COAs have calculated deprivation scores above 70, but the percentage is much lower in the South East. Although not shown in the table, the tails are concentrated in the older industrial conurbations. In the South East, Kent figures strongly at the top end, particularly COAs within Thanet. Finally, from the standard deviations, it is clear that the distribution is narrower in the South.

In summary, the results again suggest, that the probability of the most deprived areas reaching the take off point is very limited. For these areas, patterns of deprivation and segregation are likely to persist.

6.3 Long-Term Change: A Case Study of Great Saffron Hill

The evidence points to persistence in spatial patterns over a 20-30 year period, although, over much longer periods, there is some evidence of change. As noted in the quotations from the State of the English Cities report, analysis of urban change requires a very long-run perspective. Orford et al (2002), comparing data on social status from the 1991 Census and from the Booth maps in the late 19th century, highlight the stability of spatial poverty patterns over the last hundred years, but still find a degree of convergence over that period. For example, 76% of the richest wards in 1896 remain in the richest quartile in 1991, but only 55% of the poorest wards in 1896 remain in that category in 1991. Using a case study of a small street in London (rather than formal econometric analysis), it is possible to obtain some insights into the drivers of change.

Great Saffron Hill is an unexceptional, small street currently in the London borough of Camden. Its history can be traced back to the thirteenth century and was named after the fragrant crop that grew there in the 14th Century. It was also the site of the Bishop of Ely’s palace. But, by the first half of the 19th Century, Saffron Hill was notorious as a haunt of pickpockets and thieves, but it lies only a kilometre from the British Museum, the LSE and St Paul’s Cathedral. The east side backed onto the Fleet River, which was investigated as a potential source of cholera and typhus.

Much of the Saffron Hill area was torn down as part of major improvement schemes in neighbouring Clerkenwell. The Farringdon Road scheme, running parallel to Saffron Hill, was started in 1841 and was not completed until the 1860s and the development was closely tied up with the construction of the Metropolitan Line – London’s first underground railway with Farringdon as its terminus– which opened in 1863. The railway and new road completely transformed the character of the area. Much of the Saffron Hill area was swept away, displacing the residents. A second, East-West improvement scheme – the construction of the Clerkenwell Road between 1874 and 1878 - removed much of what was left of Saffron Hill. In general, slums were cleared away to be replaced with warehouses and commercial developments.

The Clerkenwell improvement schemes were, however, limited in their effect. Writing in the 1850s and 1860s, Henry Mayhew, (Neuburg 1985), highlights Great Saffron Hill as an area of low lodging houses with heavy overcrowding. Although in an era of rapid railway expansion, transport innovations were ultimately responsible for a significant reduction in population densities, in London between 1841 and 1871, paradoxically, the demolitions associated with clearance schemes for new rail operations had the initial effect of increasing
overcrowding at the centre. Rather than moving to the suburbs, the need to remain close to the place of employment meant that workers typically moved to nearby poor accommodation.

The 1881 Census provides the most detailed direct evidence of the status of Great Saffron Hill. At that time, there were 59 occupied dwellings (and numerous workshops and warehouses), housing 805 individuals (an average of 13.6 persons per dwelling). In 1881, numbers 37 and 157 were still lodging houses, the latter with 66 residents. In his monumental study of poverty in London in the late nineteenth century, Charles Booth describes the Saffron Hill area in his diaries as a combination of residential dwellings and small manufacturing workshops, factories and warehouses. But, according to Booth’s classification, the residents of Great Saffron Hill were, by no means, the poorest in the immediate area.

Table 12 summarises the population changes in the parish of Saffron Hill over the 19th century. In particular, it highlights the sharp rise in population in the first half of the century, reaching its peak around 1830. But by the end of the century, population was under half of that a hundred years earlier.

<table>
<thead>
<tr>
<th>Saffron Hill Parish</th>
<th>1801</th>
<th>1811</th>
<th>1821</th>
<th>1831</th>
<th>1841</th>
<th>1851</th>
<th>1861</th>
<th>1871</th>
<th>1881</th>
<th>1891</th>
<th>1901</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>7781</td>
<td>7482</td>
<td>9270</td>
<td>9745</td>
<td>9455</td>
<td>8728</td>
<td>7148</td>
<td>5907</td>
<td>3980</td>
<td>4506</td>
<td>3396</td>
</tr>
<tr>
<td>Popn/acre</td>
<td>243</td>
<td>234</td>
<td>290</td>
<td>305</td>
<td>295</td>
<td>273</td>
<td>223</td>
<td>185</td>
<td>124</td>
<td>141</td>
<td>106</td>
</tr>
</tbody>
</table>

Source: A History of the County of Middlesex (1911).

During the Second World War, Saffron Hill lay in the Metropolitan Borough of Holborn. Holborn was very heavily hit during the Blitz in 1940/41. Of the 28 boroughs, Holborn had the highest weight of bombs (56 kilos per hectare), the fourth highest rate of residential destruction (197 houses demolished and seriously damaged per 1,000 population) and the fifth highest casualty rate (25 casualties per 1,000 population) – see Table 4, London Topological Society, 2005. Detailed maps in this publication show that large parts of Saffron Hill were almost completely destroyed or damaged beyond repair in the Blitz. Therefore, although the street remains narrow today it is unsurprising that few of the original buildings exist. The Blitz clearly had a major impact and this shows up in indicators of overcrowding, notably the proportion of the population living with more than 1.5 persons per room. Table 13 presents information for the period 1931-2001 for the borough in which Saffron Hill lies – Holborn until 1961 and Camden from 1971. Comparable data are not available prior to 1931. The data show a gradual reduction in overcrowding in the post-war era, but a large discrete change took place between 1931 and 1951. Therefore, the evidence suggests that the major reductions in overcrowding were concentrated over a fairly short time span, but one which experienced a major external shock.
Table 13. Overcrowding in Holborn and Camden (1931-2001)

<table>
<thead>
<tr>
<th>Borough/Year</th>
<th>% of population with more than 1.5 persons per room</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holborn 1931</td>
<td>37</td>
</tr>
<tr>
<td>Holborn 1951</td>
<td>15</td>
</tr>
<tr>
<td>Holborn 1961</td>
<td>12</td>
</tr>
<tr>
<td>Camden 1971</td>
<td>8</td>
</tr>
<tr>
<td>Camden 1991</td>
<td>4</td>
</tr>
<tr>
<td>Camden 2001*</td>
<td>3</td>
</tr>
</tbody>
</table>

* refers to the proportion of households living with more than 1.5 persons per room.

Today, the bottom of the hill has undergone the most marked transformation, now consisting of new, prime office space. In the 2001 Census, the Census Output Area (COA) that includes Saffron Hill had only 240 residents (1.6 per dwelling). Although not one of the most desirable locations in London, the Super Output Area (SOA) in which Saffron Hill lies\(^{15}\) is only the 1395\(^{\text{th}}\) (out of 4765) most deprived in London. At £390,500, the average house price was 58% of the Camden mean in the first half of 2004. Therefore, over very long periods of time, Saffron Hill’s status and environment have clearly changed – from sweet-smelling fields in the 14\(^{\text{th}}\) century, through filth and crime in the 19\(^{\text{th}}\) Century, to a central business area today.

Over long periods of time, areas experience four types of innovation that change status and Saffron Hill experienced them all:

(i) exogenous innovations: examples are wars, acts of terrorism, acts of God.
(ii) endogenous innovations: migration is the most notable and London experienced long-term net out-migration towards the suburbs.
(iii) Policy innovations: these include major infrastructure changes, e.g. new road networks, new social housing estates, slum clearance and major regeneration schemes. These, of course, also affect migration patterns.
(iv) Technology innovations: for example, the Industrial Revolution, powered flight, motorised transport.

Under (i), the Blitz clearly had a major impact on London and this shows up in indicators of overcrowding in Table 13. Gregory et al (2001) find a similar pattern for England and Wales as a whole between 1931 and 1951. The story is supported by an analysis of population density gradients (Clark 1951, Ball and Sunderland 2001). In common with most major cities, density in London falls progressively with distance from the urban core. Furthermore, over time, density has fallen at the centre with the gradient becoming flatter as the city has spread out. In terms of the commonly-used exponential model, (13), \((A)\) is the hypothetical calculated density at the core and \((b)\) measures the gradient. A high value of \((b)\) implies that the density declines sharply with distance, i.e. a compact city. Small values of \((b)\) are to be expected where transport costs are low.

\[
y = Ae^{-bx}
\]  

where:
\(y\) = residential density measured in thousands per square mile
\(x\) = distance from the city centre

\(^{15}\) It lies in SOA Camden 027B.
Clark (1951) finds that in 1801 and 1841, \( b \) was high and changed little with an average value of 1.4. This is unsurprising given the heavy reliance on foot travel at the time. But by 1871, the coefficient had fallen to 0.65 as steam trains and horse-drawn omnibuses became more widely established in the capital. The coefficient continued to fall over the study period to 1939. Estimated density at the urban core rose to a peak of 800,000 per square mile in 1841, by far the highest in the sample of international cities considered by Clark. But core density fell in each census up to the Second World War. However, one of the key messages to draw from both sets of coefficients is that, although they fell gradually over the whole period from 1841, the most striking changes happened fairly quickly over the 1841-1871 period, in response to major transport innovations – these were large permanent shocks.

Smaller scale acts of terrorism than the Blitz can also have an effect on city structures. In England, the regeneration of central Manchester following the IRA bombing is a good example. Speculatively, it would be surprising if the structure of New Orleans did not undergo change, following the natural disaster of Hurricane Katrina.

Endogenous innovation arises from migration. Tables 12 and 13 show that over long time periods, major population shifts do take place, but they tend to be accompanied by other changes, notably to infrastructure. Without these accompanying developments, there are doubts whether migration flows are sufficiently large to generate major structural change, except in localities that lie close to tipping points. Since the most deprived areas experience low population turnover, they will, generally, not be in this position.

Policy and technological innovations clearly have an important impact on spatial structure. Many residential patterns originally developed along road and rail networks and, as already noted, these developments were important in explaining the out-migration of the London population from the 19th Century. Low income households are, by necessity, attracted to the locations where social housing is available and slum clearance programmes during the fifties and sixties had a major impact on residential densities. East London is likely to change, because of the 2012 Olympics and the associated infrastructure improvements.

In summary, the lesson is that, in a given year, the probability that any local area will experience a major shock (of any of the four types) sufficient to change its status is typically small; therefore patterns remain stable and the stochastically stable state contains segregated communities (Young 1998). But, over the course of centuries, the local areas are periodically subjected to major shocks that change the nature of the equilibrium. Although some of the results are consistent with the literature on complex, self-organising systems\(^\text{16}\), it is not necessary to sign up fully to a belief in complexity for the results to emerge.

7. Conclusions

*Prima facie* there is evidence that local areas undergo major long-run (over centuries) structural changes in terms of the level of deprivation. Small areas of London provide illustrative examples. But, over shorter periods – twenty to thirty years – patterns of deprivation and segregation in England have shown little evidence of change. In this paper, it is demonstrated that non-linear models, exhibiting thresholds, are consistent with both

\(^{16}\) A considerable literature now exists on city structures as self-organising systems (see Portugali 2000, Durlauf 2005, for example).
phenomena. Thresholds are also consistent with theoretical models where social interactions and contagion occur (which are expected to be important at local scales) and there is empirical evidence for non-linearity in local housing markets.

Stability results unless the most deprived areas reach a take-off point. But change relies on a series of large innovations occurring. The necessary combination is unlikely to occur on a regular basis. Analysis demonstrates the large size of the required policy interventions to induce change. Change is more likely to occur through exogenous events, such as wars or natural disasters or through major technological advances.

References:


