Paying For Good Neighbours? Neighbourhood Deprivation and the Community Benefits of Education

Steve Gibbons

October 2001

Published by
Centre for the Economics of Education
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

ISBN 0 7530 1479 3

Individual copy price: £5

The Centre for the Economics of Education is an independent research centre funded by the Department for Education and Skills. The view expressed in this work are those of the authors and do not necessarily reflect the views of the Department for Education and Skills. All errors and omissions remain the authors.

Executive Summary

It probably comes as no surprise that home-buyers pay more for a property in high-income, 'educationally-rich' neighbourhoods than they do for a similar property in poorer, low-education neighbourhoods. Property crime rates may be lower, streets safer, the physical environment may be better maintained. More importantly for families, education in the community may matter because of the influence this has on children's acquisition of education and life-skills. These effects include direct effects from adults to children through expectations, role models and skill transfers, alongside peer group effects that operate through interactions between children in the street and at school.

This study measures the price premium attracted by higher-education and higher income communities, using property price data from the Government Land Registry, qualifications data from the 1991 Census, and a commercial data set of local incomes provided by CACI Ltd.. This sample gives us near-universal coverage of property transactions and neighbourhood characteristics in England and Wales. Our approach is to estimate how property prices change from one neighbourhood to the next as the educational status of residents changes. We can place a common-sense interpretation on the change in household expenditure on property that proximity to more educated neighbourhoods generates: it is the value, in monetary terms, that a household places on improvements in educational levels in the community. This interpretation has a sound theoretical basis, and the technique has been used over many years for valuing environmental goods and the physical attributes of property. If we are prepared to assume that it is really the *education* of residents that matters – and our results suggest this – then we can infer households' valuation of educational improvements in general. This leads us to a rough estimate of the local *community benefits* of improvements in education, expressed in monetary terms.

The main results show that property prices increase by one percent in the South and East of England, and by two percent in Wales, the West and North of England, for each one percentage point shift in the proportion of higher-educated residents. Because mean education levels differ across regions, this amounts to a 0.24 percent increase in prices for a one percent *relative* change in the education of an average community in any region. This is equivalent to about £156 on 1995 national mean prices. House prices move by 0.52 percent for each one percent change in local mean incomes. Using these figures, and taking into account the empirical relationship between individual earnings and education, we deduce that education is valued as a community commodity for reasons other than its impact on incomes. We find further, that education in adult residents matters over and above other community characteristics like unemployment rates, sick rates, lone-parenthood, age, crime rates and local primary school quality. Households pay more for community educational improvements in areas where there are more owner-occupier children. Also, the proportion of home-owners with children is higher in areas where there are fewer social tenants. From this, it seems that families value community educational status as an influence on children's development and well-being.

We infer that households pay about £130 per year to purchase a ten percent improvement on average community education levels – from 19% to 20.9% higher-educated in 1995. This reflects the long-run, non-earnings related, community benefits of education. This monetary value of this benefit is at least as large as the estimates of the average private returns – the increment to earnings arising from educational improvement – which dominate the literature. Given the size of these effects, the community and other wider benefits of education deserve further analysis. Focussing only on the private returns risks seriously understating the value of education to society, and any policy decisions based on these returns alone may result in sub-optimal provision of educational services.

Note on methodology: A statistical association between property prices and local education levels or local incomes is *not* necessarily evidence of willingness to pay for neighbourhood educational status. Higher-income, more educated households will be clustered in areas with better quality housing and local amenities, simply because they *can* pay more for property than those on lower incomes. Property prices and the education of residents will both be higher in localities where there is high demand for educated workers. To overcome this problem, this paper uses two techniques. Firstly, we look only at differences between neighbourhoods which are very closely spatially associated, so minimising the geographical differences. Secondly, we predict neighbourhood education levels and incomes from the proportion and characteristics of residents in social housing. These are fixed prior to the period of our property price sample, so do not change in response to property price changes. And, there seems no reason to believe that owner-occupied housing quality, price, and home-buyer income varies in response to the local proportion in social housing – except through home-buyers perceptions of the dis-benefits of living near lower-educated, lower income people. Comparison with property-level price data that allows us to compare house-buyers with similar incomes tells us that these assumptions are correct.

Paying For Good Neighbours? Neighbourhood Deprivation and the Community Benefits of Education

Steve Gibbons

Acknowledgements

Steve Gibbons is a member of the Centre for Economic Performance and University College London.

1. Introduction

Much of the existing empirical work on 'neighbourhood effects' focuses on estimation of the impact of a child's neighbourhood on contemporaneous or subsequent outcomes – typically educational outcomes. The usual approach is to find micro data on family and neighbourhood characteristics in childhood, and on outcomes for children for these families, and to apply regression techniques to estimate the effects of neighbourhood conditional on family characteristics.[1] One drawback of this approach is that the important neighbourhood and family characteristics are often highly correlated due to spatial residential sorting attributable to preferences, land prices and housing costs. What is more, the long-run impact of neighbourhoods may be underestimated if the characteristics of parents are in part attributable to historical neighbourhood-driven processes. Measurement of these effects of neighbourhood on human capital accumulation is critical for addressing issues of equality of opportunity and the distribution of education, earnings and work across geographical space. Nevertheless, by concentrating solely on these effects we risk ignoring other, potentially substantial, economic costs of neighbourhood deprivation. The obvious example is the cost associated with higher local crime rates in areas where household permanent incomes and employment expectations are low.

A different strategy, adopted here, is to side-step measurement of direct effects on individual outcomes by looking at the overall value onwer-occupier residents place on good neighbourhoods. The model is a hedonic property price model of the type frequently used to value local amenities in the urban, environmental and housing economics literature, to estimate the implicit costs of neighbourhood educational and income deprivation. In a hedonic equilibrium, this implicit price amounts to a marginal valuation of the services provided by 'educationally rich' or high income neighbourhoods relative to 'educationally poor' or low-income neighbourhoods. These services may include neighbourhood-related inputs into the production of human capital in residents and their children, direct and indirect effects of local crime rates, and any other local consumption and production externalities. A number of theoretical models propose community sorting equilibria based on household preferences over some measure of the stock of human capital in the neighbourhood, or mean local incomes. Benabou (1993) assumes spillovers in the production of children's human capital effect individuals' willingness to pay for the proportion of high human capital communities, and those with higher marginal benefits bid up land rents in higher human wealth communities. In Fernandez and Rogerson (1997) higher income communities have higher quality education provided through higher local taxes, and in Nesheim (2001) consumers have preferences over the average schooling of residents, because this determines local school quality. The model in de Bartolome (1990) proposes sorting driven by willingness to pay for peer-group effects, though in his case the equilibrium property price premium does not reflect the price of the better peer group, but stops migration between communities in equilibrium.

The approach taken in the current work assumes that evidence of a statistical relationship between neighbourhood status and property prices can be interpreted as average marginal willingness to pay for neighbourhood effects from education, incomes, or more general neighbourhood quality externalities. A central claim of this paper is that it is *education* and its wider benefits that count. The results show that local education is much more important in the determination of property prices than local incomes, and that it remains

[1] For a survey see Gephart (1997).

a significant factor when other neighbour attributes – property crime, ethnicity, unemployment, lone parenthood and long-term sick rates – are taken into account. If we accept the evidence for this, then estimates of the implicit price of local educational composition amount to a measure of the marginal, external benefits of education in the community. On this basis, we can extend the analysis to explore the scale of the local social benefits of education in relation to the private returns typically estimated in the labour economics literature.

A key assumption underlying this work is that differences in property prices between neighbourhoods that are closely spatially associated and are otherwise observationally similar can be attributed to differences in the educational composition of the neighbourhood. Clearly, any unobserved differences across neighbourhoods in their utility-bearing attributes – physical size and quality of housing, access to amenities for example – generates observed differences in educational composition. The quantity of any local normal good is correlated with local educational composition because education is a strong predictor of permanent income or lifetime wealth. In a regression of local property prices on local characteristics, educational composition is endogenous unless all utility-bearing local attributes are included in the regression. To address this problem, our empirical approach exploits variation in the proportion of social housing across neighbourhoods as an instrument for neighbourhood educational composition, and – as it turns out – more importantly, exploits variation between neighbourhoods that are closely spatially associated.

Neighbourhood educational deprivation is measured as the proportion of highly qualified residents in postcode sectors in England and Wales, derived from the 1991 Census of Great Britain, 10% sample. This is the proportion of individuals with higher education qualifications, but is almost certainly correlated with local educational attainments in general. Although the proportion of higher-educated adult residents is fairly crude as a measure of educational deprivation, it does an adequate job of characterising the main differences between areas on the dimensions of deprivation embodied in the DETR Deprivation Indices 2000. Since higher local educational attainments mean higher local average incomes, any association between local education levels and property prices generates a corresponding association between local incomes and property prices. A national local area incomes data set, collected in the late 1990s for marketing purposes, provides a unique opportunity for investigation of this relationship at this neighbourhood level. We will see that this relationship also holds with property-level transactions data using mean incomes at a broader level of geographic aggregation.

The paper is structured as follows. Section 2 discusses the background to this work and sets it in context with its underlying concepts and existing literature. Section 3 outlines the standard hedonic property value model in the current context. Section 4 describes the data. Section 5 explains the empirical methods used. Section 6 presents the results. Section 0 concludes with an assessment of the size of community returns in relation to mean private returns per household.

2. Context

2.1. Neighbourhood effects

Residents value neighbourhood education levels and neighbourhood incomes because of the impact on a wide range of neighbourhood outcomes. Property crime rates may be lower, streets may be safer, the physical environment may be better maintained, gardens more pleasant, behaviour more orderly. More importantly for families, education levels in the community may matter because of spillovers in the production of human capital in children. These spillovers include direct effects from adults to kids through expectations, role models and skills transfers – classified as *collective socialisation* effects in the sociological literature[2]. They also include peer group effects that operate through interactions between kids of similar age in the street and at school. These effects operate to increase the expected educational attainments of children with highly educated neighbours, relative to others.

Rather than specifying all these factors in detail, we may assume that mean education levels, or mean income provides a sufficient statistic for the distribution of an unobserved composite neighbourhood good which is the object of preference (aside from the physical attributes of housing) in the choice of residential location. Let us call the ranking of a neighbourhood on this scale its *educational status*. The sociological literature and the economics literature on educational externalities frequently refers to this type of composite commodity as social capital, but as conceived (Coleman, 1988), social capital describes social interactions and community organisational structures that are not exclusively linked to educational attainment of residents in the community.

2.2. The social and community benefits of education

Although neighbourhood deprivation is multi-faceted, the key factors are income and education. It is well established that educational attainment is one of the best single predictors of long run earnings and employment. Poor educational attainments obviously mean lower expected incomes for individuals and their families, but there are also high potential external costs. These external costs of neighbourhood deprivation in education mirror the external social benefits of education, which underpin the principle of public subsidy in educational provision. The Education Reform Act of 1870 which introduced compulsory, publicly funded schooling to Britain, was motivated by liberal conceptions of education's place in a civilised and educated democracy, rather than the need for vocational skills. Nevertheless, most of the empirical work in labour economics and the economics of education focuses only on the private returns to education in the narrowest sense – the increment to earnings from additional time in education. Others have looked further at social returns conceived as external effects from human capital on production, which increase aggregate output. Whilst these are interesting issues from the perspective of policy directed to improving economic performance or addressing inequality, they say little about the value placed by society on the wider benefits education.

Private returns to educational investments include all the benefits that accrue to the individual who undertakes the education – and the individual's dependants if we are thinking of utility functions at the household level. Some private benefits, in particular increased productivity, have well defined markets and are, in principle, easily measured – the individual's wage in the case of productivity. In most empirical studies, following early examples by such as Hansen (1963) and Mincer (1974), the private returns to education are measured as the increment to earnings from additional years of schooling or from discrete categories of educational attainment. Other private returns in the labour market include effects on employment, job-search, non-wage remuneration and job-satisfaction, though not all have explicit prices. But private returns also include a wide range of benefits that are not traded in any markets; Haveman and Wolfe (1984) provide a fairly exhaustive taxonomy. These non-market effects include productivity at home, own-health benefits, the enjoyment

[2] Jencks and Mayer (1990).

value of leisure time, effects on the education and welfare of own offspring, effects on fertility, plus the consumption value of education.

Social returns are usually defined as benefits to other members of society arising from an individual's school achievements, or participation in higher education. There will be social benefits if there are externalities in production, whereby the productivity of others is increased by association with more educated workers – by more productive work relations, by direct transfers of knowledge, or where an educated community stimulates technical innovation. This type of model is popular in the growth literature, following Lucas (1988). Effects on production may also operate through externalities in human capital accumulation. Individual human capital accumulation may spill over to increase the human capital accumulation of other adults in the community, and the educational attainments of children outside the person's own family. However, alongside these benefits which accrue to society through increased aggregate production and growth we must consider a catalogue of social benefits which are welfare improving, but which may have little or no effect on wages, or output. Most of these non-market social benefits are public goods that are more or less geographically localised: social cohesion, citizenship, crime reduction, improved public health.

These benefits, along with any productive externalities in the formation of human capital, are perhaps better referred to as the *community benefits* of education. These are the educational benefits addressed in this paper.

The claim that education or income is the key characteristic of interest to households in the evaluation of neighbourhood quality – or is a sufficient statistic for neighbourhood quality – provides a basis for measuring the long-run, social, community-based returns to education. This needs some further justification. A reasonable counter-claim is that education merely proxies other behaviours of individuals which are unobserved in the data – drug abuse, vandalism, criminal activity – which impose costs on others in the neighbourhood. We must assume that these characteristics originate in lack of education and income: if these characteristics are innate or otherwise fixed prior to educational decisions, and an individual's educational attainments are determined by these characteristics, then we cannot infer the social returns this way.

One possibility is that parental characteristics and social background generate initial conditions – psychological or economic – which inhibit an individual's acquisition of education, or mean that any education acquired is valueless in the social context, even under a supportive policy regime. In this setting, educational policy will have relatively small effects on educational outcomes and will have few benefits in the short run. Nevertheless, there may be long run effects if even small improvements in the parents' generation means a better setting for a child's acquisition of education. If acquisition of education is mediated solely through genetic or other innate and unalterable characteristics, then we cannot interpret property price effects that originate in preferences for these characteristics or their benefits as monetary realisations of the social benefits of education. Property prices still reflect the perceived benefits of a neighbourhood 'cleanup', but the mechanisms for achieving this are not education-based. This view might, for example, find support amongst those who consider criminal behaviour as fundamentally innate, and that lower educational attainments amongst participants in crime is indicative of a preference for crime over legitimate activity. If the distribution of property prices and education levels are related through fear of crime, or the costs of attacks on property, then the implicit price of educational status measures a transformation of the social benefits of crime-reduction policy.

Willingness to pay for higher-educated or high income neighbours will also overstate the community benefits of education if households place value on their location in the distribution of neighbourhood status. If high-education/high-income households experience no direct costs from living amongst low-education/low-income households, but benefit solely from the status conferred by living in relatively wealthy neighbourhoods, then policies that increase educational attainments by compressing the distribution may inadvertently generate net social costs.

2.3. Precedents in the literature

2.3.1 Neighbourhoods and property value

Estimation of neighbourhood incomes and educational status on property prices has a long history in the US. Many early studies of the factors affecting property values include some neighbourhood characteristics as covariates, though the response to neighbourhood is not usually the main parameter of interest. Some examples of early studies in the US literature that emphasise the role of neighbourhood externalities on property values follow. Kain and Quigley (1970) estimate that prices of owner-occupied housing increase by 7.8%, and rents increase by $2.55 for each additional year of mean adult education in the Census tract, using a small sample in St. Louis. Berry and Bednarz (1979) found that a $1 increase in median census tract incomes increases the value of single–family homes in Chicago by abut $0.70. Both studies condition on a number of neighbourhood and property attributes. Freeman (1979) emphasises the importance of socio-economic and other neighbourhood variables as determinants of property values.

A number of studies look specifically at the effect of social housing projects and other property development on local property prices. An early example is Schaffer (1972), who looks at the impact of housing construction for low income families under the US 1961 "Below Market Interest Rate" scheme using treatment and control sites in Los Angeles. He finds no significant difference between the price trends at the two sites, probably due to the fact that most of the new residents already lived locally. Ding, Simons et al. (2000) are more concerned with the impact of local residential investment on property prices. Using data on Cleveland, Ohio, they find a $0.87 increase in property prices with each $1 of median census tract income (in 1990) corresponding to an elasticity of 0.36 at the sample mean. Their estimates also imply an elasticity of –0.04 with respect to the census tract proportion of African-Americans. They also report a negative, but insignificant effect from the proportion in poverty. Crime rates attract a strong negative coefficient, corresponding to an elasticity of –0.13.

Munneke and Slawson (1999) are interested in potential negative externalities from mobile home parks in one parish in Louisiana and estimate a two-step selectivity model to adjust for the endogeneity of mobile home park location. Location within 0.25 miles of a mobile home park in a residential area leads to a 5% decline in the value of a single family dwelling, relative to properties located between 0.25 and 0.5 miles radius. They offer no theory as to the cause of this externality, but the perceived type of mobile home residents is presumably a key issue. Two other recent studies investigate the impact of social housing programs in the US. Lee, Culhane et al. (1999) consider the effect of public and assisted housing on property values in Philadelphia. The authors of the first paper find negative effects from proximity to public housing developments and other assisted housing schemes, but these effects largely disappear, or their sign is reversed once neighbourhood composition controls are included. They find no statistically significant effects from the physical type of development, which suggests that it is the characteristics of residents and not the physical structure of social housing that generates the externality. Log property prices increase by 1.6% for each thousand dollars of neighbourhood median incomes – an elasticity of 0.41. Galster, Tatian et al. (1999) look at the impact on property prices of neighbours in receipt of

"Section 8" certificates, which entitle low-income households to a housing subsidy. They use a model with spatial fixed neighbourhood effects to find heterogeneous impacts from assisted housing programs in Baltimore, with adverse effects in lower price areas, but positive impacts from small-scale programs in higher valued tracts. Interestingly, the authors conducted focus group studies in four communities with distinct socio-economic compositions, to gauge residents' opinions of social housing developments. Some respondents expressed sensitivity to the physical condition of rental accommodation, with a fear that assisted housing brought physical decay and vandalism. Many groups expressed clear antipathy to problem tenants, believing that those in socially assisted housing had different values and standards than what the current residents desired for their neighbourhood. Many feared that subsidised housing brought increased crime.

Few studies on the value of neighbourhoods exist for Britain – due to the lack of data. One example is Cheshire and Sheppard (1995), who find positive amenity values in Reading from local schools, the proportion of white collar workers and the proportion in non-Afro-Caribbean ethnic groups. They estimate aggregate land values (over the geographical space of their sample) of £43,430 attributable to schools, and £81,820 attributable to social and ethnic composition, but offer no estimate of the mean benefits per household.

2.3.2. The social and non-market returns to education

No existing studies propose a link between the willingness to pay for good neighbourhoods and the measurement of community benefits of education. However, there are a number of approaches to measuring other benefits beyond the traditional private market returns on earnings. Since Lucas (1988), who discussed the potential role of human capital externalities in economic growth, a strand of empirical research has emerged which has tried to measure the impact of state, region or country average education levels on wages, productivity and growth. A few examples will give the flavour of this research programme.

Weale (1992) uses private returns and international comparisons of growth rates and educational attainments to suggest that long run social returns incorporating spillover effects on growth rates could be two to three times the magnitude of the private returns. Jaffe (1989) looks at the social rate of return to university research in the form of state-specific spillovers into corporate patents, and finds positive effects with elasticities as high as 0.3 in some industries. Acemoglu and Angrist (1999) find strong effects on wages from state education levels, conditional on individual education using OLS estimates on US Census data, but these social returns become weak and insignificant once they instrument the educational variables with state compulsory school attendance laws and individual date of birth effects. Ciccone and Peri (2000) find negative effects from city education levels on individual wages using data from 173 US cities in 1970, 1980 and 1990. Using data on average wages in cities, they find insignificant, near-zero, effects on wages, but small positive effects on productivity of around 1%.

More directly related to the work in hand is Haveman and Wolfe (1984), who present a meta-analysis of earlier work to compute an approximate figure for the annual value of an additional year of schooling based on non-marketed effects on the production of children's cognitive development, contraceptive use, efficient budget allocations, criminal apprehension and health. Their technique is based on obtaining the shadow price of the non-marketed input from the ratio of its marginal product to that of another, marketed input with a known price. Their figures suggest a value of social and private non-marketed benefits in the order of $5000 in 1975 – a value of a similar order to the annual value of a year of schooling in standard private rate-of-return estimates.

3. The Hedonic Model

We shall use a standard hedonic property value framework to assess the implicit price of neighbourhood educational and income composition. This framework has been employed frequently in the environmental, land and urban economics literature to price local environmental amenities. Individuals are assumed to have weakly separable preferences over a set of housing and location characteristics. A dwelling comprises a bundle of these attributes. Sellers and buyers with different incomes and different preferences over local school performance and other property characteristics are matched efficiently by the property market. This leads to an implicit price surface that traces out the locus of efficient transactions in price-characteristics space. See Rosen (1974) for the classic exposition.

Following the standard hedonic, property value model, we specify household preferences as:

$$U = U\left(c, x, y^c(x), \mathbf{q}, \mathbf{l}\right) \tag{1}$$

where c is a numeraire composite consumption commodity, x is the measure of neighbourhood status – either the neighbourhood proportion higher-educated or log mean neighbourhood incomes – $y^c(x)$ is a human capital production function for children in the household, $\mathbf{q}$ is a vector of structural housing characteristics, $\mathbf{l}$ is a vector of locational characteristics. House prices are determined as a function of the same attributes, where the attributes are traded at a set of exogenous prices $\boldsymbol{\theta}$ fixed by demand and supply equilibrium at a broader geographical level:

$$P_h = P_h\left(x, \mathbf{q}, \mathbf{l}; \boldsymbol{\theta}\right) \tag{2}$$

The household lifetime budget constraint is:

$$y = c + P_h\left(x, \mathbf{q}, \mathbf{l}; \boldsymbol{\theta}\right) \tag{3}$$

Assuming the choice space is continuous so that households can purchase their optimum bundle the first order condition for x is:

$$\frac{\partial U/\partial x + \partial U/\partial y^c \cdot \partial y^c/\partial x}{\partial U/\partial c} = \frac{\partial P_h}{\partial x} \tag{4}$$

This standard condition justifies the use of an estimated implicit price function $P_h(\cdot)$ in the estimate of the marginal willingness to pay for local educational status. If consumers are heterogeneous in their marginal benefits from x then stratification into high and low x communities can occur, and $P_h(\cdot)$ can be non-linear in x. Without information on human capital of children, it is not possible to identify separate contributions of educational status to human capital formation and consumption value in the implicit price, only the sum of the marginal benefits. But, given an appropriate specification of P_h and individual level data on house prices, neighbourhood, housing and locational characteristics, it is possible to estimate the overall willingness to pay for marginal improvements in neighbourhood educational status or local mean incomes, for given neighbourhood quality x.

In the case where the community is valued purely as an input into the production of children's human capital and lifetime wealth, marginal willingness of parents to pay for x will be the marginal effect on the present value of their children's total future earnings. Because of its local public good nature, families with more children are willing to pay more for neighbourhoods with high levels of our commodity. Families will bid up the price of improvements in the neighbourhood until the marginal cost equals the sum of the marginal benefits over all their children. The alternative is to divide expenditures on private goods that improve the welfare of children, or to distribute income directly to children in the form of transfers. An implication of this is that the average number of children per household, or the proportion of households with children in a neighbourhood, will be increasing as neighbourhood status increases exogenously. It follows that the implicit price of neighbourhood quality will increase as the mean number of children per family increases.

4. Description of the Data

Since the empirical methods are designed to suit the data, it will help to describe the data first. British data on individual property transactions with local area identifiers is not readily available. Instead, we must use locally aggregated data available from the Government Land Registry. This covers most market value property transactions in England and Wales, aggregated to postcode sector level. In the UK, postcodes contain up to seven alphanumeric characters, and contain four hierarchical components. The first two alphabetic characters define the *postcode area*, the broadest postal zone. Examples are N, EX YO representing North London, Exeter, York. Within postcode areas, the next level down is the *postcode district*. A single or two-digit number following the postcode area defines this. Examples are N6, EX24, and YO10. A single letter further subdivides some postcode districts in central London. Below this, we have *postcode sectors*. This is the unit of observation in our house price data set, and the unit adopted here as a neighbourhood identifier.

This Land Registry data is disaggregated by property type – detached, semi-detached, terraced, flat/maisonette – but this is the only information provided about the characteristics of properties included in the price data. At the time of writing, this data set is available from 1995 to 2000. It contains mean house prices and total sales volumes for each dwelling type in each postcode sector, where annual sales numbered 3 or more. Properties under £10,000 and over £1,000,000 are excluded. This amounted to only 0.5% of all property sales in 1999. Sales at non-market value transactions are also excluded. This is an advantage in our application, because market prices will not be contaminated by discounted sales of council houses to tenants under the Right to Buy scheme introduced in the 1980s.

Micro-spatially aggregated data has an advantage over property level data in the current application because we are only interested in the variation in prices attributable to mean neighbourhood characteristics. What we do need though are property prices and neighbourhood attributes at the same level of disaggregation. Sources of information on educational deprivation in local areas are limited. The most up to date data is combined into the Education, Skills and Training domain of the DETR Indices of Local Deprivation 2000.[3] This index is generated at census ward level, not postcode sector level and there is no correspondence between these two geographies. An alternative source is the 1991 Census

[3] This index combines a number of dimensions of educational deprivation – working age adults without jobs, over-16s not in full time education (DSS), applicants for higher education (UCAS), primary school performance, children with English as an additional language, and primary school absenteeism.

Small Area Statistics. This provides a count of the number of over-18s with degrees, diplomas and other high qualifications, based on a 10% sub-sample of the census population.[4] The age of the census data and the 10% sampling scheme are a drawback, but in compensation we have a straightforward interpretation of the relationship between property prices and the proportion of highly qualified adults, and the fact that re-aggregation to postcode-sector level rates is fairly straightforward. The 1991 census also provides an accurate measure of the proportion of households in social housing – required as an instrument for educational status – plus grid references, housing and various other local characteristics. For the central results presented in this paper, I match the Land Registry property price data to 1991 census data, re-aggregated from Enumeration District level to postcode sector level using the Postcode-Enumeration District lookup tables available from the Census Dissemination Unit.

Local income data for Britain is also scarce. For this we must turn to a commercial data set produced by CACI Ltd. for marketing purposes. Their survey is available for 1996, 1999 and 2000 (though only the 1996 and 1999 surveys are used here) and each wave is based on over 4 million households. Incomes are modelled by CACI down to individual postcode level using 1991 census data. A postcode sector comprises 2700 households on average. In 1999, the mean number of actual observations of incomes used for the postcode sector mean (not imputed) is 436 with a sample mean income of £21,860 and a standard deviation of household incomes of £15,000. The standard error of the postcode sector mean would be around £720, or 3.3% of the overall mean. This gives some confidence that the data, although partially imputed, is reliable at postcode sector level.[5]

More data on property values is available from the Survey of Mortgage Lenders, an annual 5% sample (around 25000) of mortgage transactions. This has the advantage of property level prices, dwelling characteristics and total household incomes, but the disadvantage of broader, Local Authority geographical identifiers. Still, we can use estimates from this data set for comparison with the baseline results.

5. Empirical Methods

5.1. Empirical model

As discussed above, our property price data set has no household level data. Instead, in the Land Registry data set, annual housing transactions are aggregated to provide an average of prices in four property-type categories at postcode sector level. A sample of k transactions on a house of type r will contain a mix of structural characteristics $\mathbf{q}$. Assuming that the sample value of the price of houses of type r, in postcode sector i, at time t, with mean characteristics $\bar{\mathbf{q}}$ is the market price of a representative property, then the household hedonic price function is representable by a hedonic price function at the neighbourhood-house-type level. There is

[4] The relevant question is number 19 in the Census form, which asks for details of post-compulsory-age educational qualifications of all persons over the age of 18 in the household on Census night (21-22 April 1991). The Census Small Area Statistics contain counts of persons with higher degrees, degrees, or diplomas, nursing or teaching qualifications, based on a random sample of 10% of the responses from each Census Enumeration District (a much smaller geographical unit than the postcode sector).

[5] As a safety check, we can compare the CACI data with New Earnings Survey data for 1995/1996. Unfortunately the NES records postcode of employment, not residence, and includes earnings only, not family incomes, so we would only expect moderate correlation. Aggregating to postcode district level, we find a correlation coefficient of 0.36. At postcode area level, this increases to 0.77.

no detailed information on structural characteristics for our sample of house transactions. One option is to proxy the characteristics with census data on owner occupied housing in 1991. The only census variables which could reasonably be treated as exogenous – not, like housing amenities, subject to change in response to shifts in residential composition – are those that give the distribution of rooms across households in the postcode sector.

In the tradition of the property value literature, the models presented here use the natural logarithm of property prices as the dependent variable. An unknown function $g(\mathbf{l}_i, t)$ maps locational characteristics to house price in each time period. This specification obviously imposes the constraint of a constant percentage response in house prices to a one percentage point absolute increase in the proportion of qualified residents, or a constant elasticity with respect to local incomes. Entering education linearly, and income in natural logs, is consistent with the usual Mincer-type earnings function which specifies log incomes as linear in educational attainments. The specification of the log-price of a house of type r in neighbourhood i at time t is then:

$$\ln P_{irt} = \alpha + \beta_x x_{it} + g(\mathbf{l}_i, t) + h_r + u_{irt} \qquad (5)$$

where there are fixed effects for the four housing types h_r.

5.2. Estimation strategy

Estimation of a full structural specification of the mapping of neighbourhood characteristics $\mathbf{l}$ to house prices requires data on local amenities, local housing characteristics, the proximity of neighbourhoods to transport services, local labour demand, environmental quality and other unknown local goods. The function $g(\mathbf{l}_i, t)$ could then be replaced by a specific function of available covariates. This is the traditional method used in property value models, with ad-hoc inclusion of a broad, though potentially incomplete, set of explanatory variables. In the absence of this data and any prior knowledge about exactly what should be included, we can replace the mapping of $\mathbf{l}$ to house prices with some specification that maps neighbourhood to house prices through the location of the neighbourhood in geographical space and time.

The approach adopted here is to estimate $g(\mathbf{l}_i, t)$ as a spatial fixed effect using a non-parametric kernel regression procedure. This estimates the average value of property prices and the regressors at a postcode sector, as a distance-weighted average of the values in the surrounding postcode sectors. Estimation is then based on linear regression using the deviations of the observed values of property prices and the regressors from the estimated expected value surfaces over geographical space. The grid reference co-ordinates of a geometric central point in postcode sector determine the spatial location of an observation and the weights that should be applied to other observations. Observations in closer proximity receive the highest weights. The advantage of this method over, say, using dummy variables for groups of postcode sectors in close proximity, is that it centres the comparison group on the observation postcode sector and allows flexibility in the choice of group radius. This amounts to deciding on a bandwidth b for the kernel, which will determine how rapidly the weights decrease as we move away in space from a given neighbourhood observation. Where there is more than one year of data, we can allow time effects via a separate non-parametric surface for each period, so:

$$g(\mathbf{l}_i, t) = \sum_t d_t \cdot g_t(\mathbf{l}_i) \qquad (6)$$

where d_t is a time dummy. This allows for differential growth in house prices across geographical space.

This *smooth spatial effects* estimator (SSE) is also used in Gibbons and Machin (2001) for pricing primary school performance. Expressing the model in deviation from estimated expected values, given the spatial location, *c1*, *c2* and the choice of bandwidth *b* for the comparison group:

$$[\ln P_{irt} - m(\ln P_{irt} \mid \mathbf{c}, b)] = \beta[x_{it} - m(x_{it} \mid \mathbf{c}, b)] + \boldsymbol{\gamma}'[\mathbf{w}_{irt} - m(\mathbf{w}_{irt} \mid \mathbf{c}, b)] + \varpi_{irt} \qquad (7)$$

The locational mean of a variable y, $m(y \mid c, b)$ is estimated by the bivariate Nadaraya-Watson estimator

$$m(y \mid \mathbf{c}, b) = \frac{\sum_i^N y \times k\left\{(\mathbf{c} - \mathbf{c}_i)' \mathrm{B}^{-1} (\mathbf{c} - \mathbf{c}_i)\right\}}{\sum_i^N k\left\{(\mathbf{c} - \mathbf{c}_i)' \mathrm{B}^{-1} (\mathbf{c} - \mathbf{c}_i)\right\}} \qquad (8)$$

where B is a 2 × 2 bandwidth matrix, e.g. $b^2 \times \mathbf{I}_2$, and $k\{\cdot\}$is a multivariate kernel. For the Gaussian kernel this is $k\{\mathbf{v}\} = 2\pi^{-1} \exp\{-0.5\mathbf{v}\}$. Parameters β, γ and their variance covariance matrix can then be estimated by OLS on the transformed variables.

As the bandwidth *b* tends towards zero, the estimator approaches an estimator with postcode sector fixed effects. Since we have no time-series variation in the Census education measure, and very little in our incomes data (98.3% of the variation is cross-sectional), this is inappropriate. At the other extreme, an infinite bandwidth is equivalent to the OLS estimator, with the function $g(\mathbf{l}_i)$ estimating a constant. Since there is enormous variation in postcode sector land areas and household density, a common bandwidth for all observations will lead to inconsistent estimates. The estimated price and regressor surfaces will be over-smoothed in areas of high household density and low land area postcode sectors, and under-smoothed in rural areas. Consequently, we must weight the neighbourhood bandwidth using data on household density matched in from the 1991 Census. Fixing the number of households *n* in a circular spatial group of radius b, gives us a bandwidth weighting rule dependent on housing density *h*:

$$b = \sqrt{\frac{n}{\pi h}} \qquad (9)$$

The baseline results in the paper use bandwidths corresponding to 3400 households, but comparisons are made with other bandwidth choices[6]. Sensitivity to bandwidth choice can be tested by the usual Hausman test for equivalence of parameters in alternative estimators. Too narrow a bandwidth gives a consistent but inefficient estimator; too wide a bandwidth results in inconsistent estimates.

[6] Hardle (1990) presents bandwidth adjustment factors for comparing smoothers using different kernels. The 43% downward adjustment is based on achieving similar smoothing to a uniform kernel with unit bandwidth, i.e. if we want equivalent smoothing to a uniform kernel of radius equal, on average, to two postcode sectors (6000 households) we need a Gaussian bandwidth of 0.57*6000 = 3420 households.

As will be discussed in Section 5.4, we need instruments to identify the implicit prices. In IV estimation, instruments are taken as deviations from the estimated local means. The final partial linear smooth spatial fixed effects IV estimator is:

$$\hat{\beta}^{SSE-IV} = \left[\tilde{\mathbf{X}}'\tilde{\mathbf{Z}}\left(\tilde{\mathbf{Z}}'\hat{\Omega}\tilde{\mathbf{Z}}\right)^{-1}\tilde{\mathbf{Z}}'\tilde{\mathbf{X}}\right]^{-1}\tilde{\mathbf{X}}'\tilde{\mathbf{Z}}\left(\tilde{\mathbf{Z}}'\hat{\Omega}\tilde{\mathbf{Z}}\right)^{-1}\tilde{\mathbf{Z}}\tilde{\mathbf{p}} \quad (10)$$

where **X** is the regressor matrix, **Z** is the full instrument matrix and **p** the house-price vector. The tilde indicates deviations from the non-parametric estimates of the smoothed surface means in the smooth spatial effect models. I estimate the matrix $\tilde{\mathbf{Z}}'\hat{\Omega}\tilde{\mathbf{Z}}$ using the Huber-White method, with clustering on postcode sectors to allow for the fact that we have multiple house type (and sometimes time periods) in each postcode sector. The variance covariance matrix is estimated by the inverse of the first term in square brackets.[7]

5.3. Estimation of non-linear responses to neighbourhood composition

The model in (5) imposes a log-linear relationship between property prices and the proportion of highly qualified neighbours. Some empirical verification of this assumption is in order. Non-linearities in the implicit price function will have implications for evaluation of the aggregate social benefits of an increase in educational attainments. Evidence of non-linearities may enrich the empirical analysis by revealing threshold effects in the spirit of 'contagion' theories of neighbourhood deprivation which have been popular in the sociological literature – see Jencks and Mayer (1990) or Crane (1991). If contagion or epidemic theories are correct then home-owners should be indifferent to neighbourhood educational composition until education levels fall below some critical threshold.
In order to check for such non-linearities we must generalise the semi-parametric estimation procedure above, to estimate:

$$\ln P_{ir} = g\left(x_i, c_{1i}, c_{2i}, b_i\right) + \gamma'\mathbf{w}_{\mathbf{ir}} + u_{ir} \quad (11)$$

Visual representation of the relationship between $\ln P_i$ and x_i is infeasible in the general case. Instead, a function $h(x)$ can be estimated as the average relationship between expected prices and x_i, averaging over the distribution of spatial co-ordinates, i.e.

$$h(x_i, b) = \iint_C g\left(x_i, c_{1i}, c_{2i}, b\right) f\left(c_1, c_2\right) dc_1 dc_2 \quad (12)$$

where C is the support of $\left(c_{1i}, c_{2i}\right)$ in the sample, and $f\left(c_{1i}, c_{2i}\right)$ is their joint density. The computational procedure is as follows:

1. Estimate the linear coefficients $\boldsymbol{\gamma}$ in the model (13) below, replacing $m(\cdot)$ with a 3-regressor kernel regression estimates with observation-dependent bandwidths b_i for c_1, c_2, and a fixed bandwidth for x:

[7] I compare with bootstrap standard error estimates in one case to assess the accuracy of the standard errors.

$$[\ln P_{irt} - m(\ln P_{irt} \mid \mathbf{c}, x, b)] = \boldsymbol{\gamma}'[\mathbf{w}_{irt} - m(\mathbf{w}_{irt} \mid \mathbf{c}, x, b)] + \varpi_{irt} \tag{13}$$

2. Estimate $\hat{h}_m(x)$ by kernel regression of $(\ln P_{ir} - \hat{\gamma}'\mathbf{w}_{\mathbf{ir}})$ on x, c_1, c_2 at a number of grid points $\dot{x}_g$, all at a fixed co-ordinate-pair $(\dot{c}_{1m}, \dot{c}_{2m})$. This co-ordinate pair is drawn at random from the sample.

3. Re-calculate $\hat{h}_m(x)$ at M different co-ordinate pairs drawn at random from the sample.

4. Calculate $\hat{h}(x) = \frac{1}{M}\sum_{m=1}^{m=M} h_m(x_i)$, that is the average of the M kernel regressions over the sub-sample of randomly chosen, within-sample, spatial locations at which the estimated joint density $f(x, c_1, c_2) \neq 0$.

Since in this application, educational composition x is treated as endogenous (see Section 5.4 below), it is replaced by the generated regressor:

$$\hat{x}_i = \hat{x}(z_i, c_{1i}, c_{2i}, b_i) + \hat{\gamma}'\mathbf{w}_{\mathbf{i}} + \hat{h}_r \tag{14}$$

where z is a suitable instrument, $\hat{x}(z_i, c_{1i}, c_{2i}, b_i)$ is estimated by kernel regression, and the other parameters are estimated using the partial linear model described above. If $\hat{h}(\hat{x})$ is to be a good representation of $\hat{h}(x)$, we require that the instrument is continuous, is a strong predictor of x, and that $\hat{x}$ has a similar support to x. As discussed in Section 5.4, the proportion of social tenants is the main instrument, and this satisfies these requirements. Rilstone (1996) discusses the use of generated regressors in non-parametric estimators, and their asymptotic properties.[8]

5.4. Identification strategy

Inclusion of any household personal characteristics on the right hand side of a hedonic model causes problems. The ability of households to move across space implies that household characteristics are almost certainly endogenous in a property price equation – variation in unobserved determinants of property prices drives the variation in characteristics of residents. Interpretation of estimated coefficients on household or individual characteristics is difficult, and their inclusion can lead to biased and inconsistent estimates of the parameters of interest. This is particularly true of characteristics that are highly correlated with household income, in that lower land prices will attract those with lower incomes.

An analogous problem arises if we include community characteristics that are correlated with home-owner household incomes. The household level relationship between incomes and housing expenditure is replicated at an aggregate level if we include local mean incomes, or other local demographics that are correlated with household incomes. A

[8] Note that no adjustment is made to the confidence intervals to take account of this generated regressor. Since the asymptotic distribution of this semi-parametric estimator is complex, I compare the analytical standard errors with bootstrap estimates for one case – see Appendix C. The additional computational effort required to compute bootstrap standard errors for all the estimates is hardly worthwhile, since the main purpose of the exercise is to show up any non-linearities in $h(x)$.

regression of property prices on local mean income gives us a parameter estimate which measures the response of property expenditure to *own* income, rather than home-owners' valuation of local incomes as a commodity. Similarly, neighbourhood education levels will be highly correlated with own wealth or permanent components of income.

The structure of the problem is common to all endogenous regressor models. The relationship of interest is:

$$\ln P_{irt} = \alpha + \beta_x x_{it} + g(\mathbf{l}_i, t) + h_r + \rho v_{it} + \varepsilon_{irt} \qquad (15)$$

Where v_{it} is the component of neighbourhood choice which is observed to property buyers, but unobserved to the econometrician, and ε_{it} represents components of property price formation which are unobserved to both – optimisation errors, local estate agent activities for example. But neighbourhood status x is partly determined by migration of home-owners between neighbourhoods, because of selection on unobserved components in the determination of property prices, underlying land prices or structural differences for example.

$$x_{it} = \phi + \lambda' z_{it} + g(\mathbf{l}_i, t) + v_{it} + \xi_{it} \qquad (16)$$

Hence, $E[\rho v_{it} + \xi_{itr} \mid x_{it}] \neq 0$ and regression estimates are biased. Identification of the implicit price of a local amenity which is not exogenous to other determinants of residential land and building values requires one of two strategies. Firstly, we can saturate the model with property descriptors and exogenous local characteristics, in the hope that unobserved determinants of property prices are purely random, and not driven by unobserved housing characteristics or local amenities, i.e. $E[\rho v_{it} + \xi_{itr} \mid x_{it}] = 0$, so $v_{it} = 0$. This is the method implicitly adopted by most researchers in the housing economics field, hence the extended vector of covariates presented in many property-value models. This type of estimator tries to achieve conditional independence of the error term and the characteristic of interest[9]. The weakness of this approach is that we need a lot of property characteristics and, in the absence of any spatial controls, a fully specified model of local determinants of land price – distance to the central business district, distance to modes of transport, distance to other local amenities. Since property characteristics exhibit a high degree of mutual correlation, interpretation of the parameters can be difficult. What is more, the determinants of property prices which are left unobserved to the researcher must also be unobserved to property buyers, or considered irrelevant, if they are to be truly exogenous to incomes. Expenditure on any attributes of the local environment or physical structure of local properties, which are normal goods and are observed by buyers, will be positively correlated with incomes.

Estimation on differences from local expected values partly overcomes the identification problem by removing most of the variation attributable to local labour markets, local environmental goods, and transport services. This assumes that v_{it} is subsumed in $g(\mathbf{l}_i, t)$. A more robust approach is to combine this estimation strategy with instrumental variables for the local characteristic of interest, using some columns of the vector z_{it}. In the current context, we need local characteristics which are correlated with local educational composition or local incomes, but which affect the education and incomes of home buyers only through their influence on local education or income, valued as an amenity. Candidate

[9] This traditional regression approach is analogous to matching estimators of treatment effects, but with restrictions on functional form.

instruments are the proportion and characteristics of households in *social* housing – see Appendix A. The identifying assumption is that the incomes of home-owners are locally uncorrelated with the proportion, incomes and education of tenants in social housing – except in so far as the presence of low-income, low education tenants in social housing generates an externality that home buyers are willing to pay to avoid. The presence of capital market constraints dictates that home-owner incomes will also be lower in areas with high proportions of social housing, but only because of the influence of the neighbourhood on property prices.

Although the proportion of social tenants is a satisfactory instrument for educational attainments and local incomes, we would prefer some over-identification, if only to allow a test of the specification. Any characteristics of social tenants which are correlated with educational attainments and incomes (conditional on the proportion of social tenants) will suffice. As it turns out, a good additional instrument is the proportion of social tenants from ethnic groups originating in the Indian sub-continent. These groups have, on average, higher qualifications than social tenants from other ethnic groups, but the proportion of these groups is uncorrelated with property prices once we control for local ethnic composition in the property price equation.

6. Results

6.1 Summary and assessment of the data

6.1.1. Property price data

The results in this paper are presented separately for three broad geographical regions of England and Wales. These regions correspond to grouped Standard Statistical Regions:

East and South East:	London, South East (rest), East Anglia
Wales, West and South West:	West Midlands, South West, Wales
The North:	East Midlands, Yorkshire and Humberside, North, North West

This scheme separates areas with widely differing property market characteristics, but retains a mix of rural, urban and metropolitan geographies in each group. This enables investigation of differences across regions, without over complicating the presentation of results. Roughly speaking, these areas are grouped according to property price growth in the late 1990s.

Table 1 summarises the main variables in our data set. The property price sample includes only those properties with recorded postcodes. This sub-sample under represents higher price properties in 1996 when compared with the full sample used by the Land Registry or the random 5% sample conducted by the Society of Mortgage Lenders. The postcode sector data under-represents higher priced detached houses and flats in all regions, probably because it under represents new high-end properties. The Land Registry confirmed that many new properties are registered without postcodes, so are missing from the postcode sector level data. The censoring of these groups in the dependent variable has the potential to downward bias our regression estimates. Given that the difference between the means in the postcode sample and the full sample is only around 5% this should not be a serious problem.

6.1.2. Neighbourhood education data

The Indices of Deprivation 2000 published by the DETR provide the most up to date indicators of deprivation in education, income, employment, health and housing, child poverty, and access to services. The ward level basis of these indices is not compatible with our property price data at postcode sector level, but we can compare the indices with our Census education measure at ward level. Appendix B shows that the educational composition variable from the 1991 Census is moderately correlated with the current deprivation measures, and does a good job of predicting educational deprivation when instrumented with the proportion in social housing.

Is there any direct evidence that residents prefer more educated neighbourhoods? Regressing a ward-level indicator[10] of neighbourhood dissatisfaction on the ward proportion with high qualifications suggests a 0.01% (s.e. = 0.0047%) decrease in the proportion expressing dissatisfaction as the proportion of highly qualified residents increases by 1% – an elasticity of 0.016 at the mean. This result is unchanged if we include other key census variables – the proportions professional, unskilled, unemployed, non-white, lacking housing amenities, in social housing, in agricultural employment, plus household density and average property size. The ward proportion with high qualifications is the *only* statistically significant coefficient (at the 5% level) in this regression[11]. Admittedly, the magnitude of the effect is small using this data, but educational composition seems to be one of the stronger candidates amongst local factors for a contributor to residents' self-reported perceptions of satisfaction with their neighbourhood.

6.1.3. Assessing the instruments

As discussed in Section 5.4, identification of the implicit price of neighbourhood education or neighbourhood incomes requires an instrumental variables approach. The main proposed instrument is the postcode sector proportion of households in social housing. Some over-identification is obtained by including the proportion of these social tenants in ethnic groups originating from the Indian subcontinent. Both are highly significant in regional within-area[12] regressions of educational composition on the exogenous variables and instruments, with an F- statistic of 240 for Wales and the South West, 392 for the South and East, and 321 for the North of England. As the proportion in social housing in 1991 increases by 1%, the postcode sector proportion of all residents with diplomas, degrees and above decreases: by 0.28% in the South and East, by 0.17% in the North, and by 0.22% in the West. The within-area R^2s are 0.32, 0.41 and 0.38 respectively, so the proportion in social housing explains a considerable proportion of the local variation in qualifications. Educational attainments increase with the proportion of social tenants from Indian sub-continent ethnic groups, except in the Northern regions where the relationship is negative. Appendix B presents evidence on the proportions of these tenancy and ethnic groups with higher education qualifications.

Our identifying assumption is that education and incomes of home-buyers and social tenants are locally uncorrelated, except through the influence of the proportion of low-education/low-income social tenants on property prices. Obviously this will not be true over larger areas, in which case differences in labour market opportunities and earnings will affect

[10] Burrows and Rhodes (1998) combine Survey of English Housing and 1991 Census data to model the geographical distribution of neighbourhood dissatisfaction in terms of the percentage of households in each ward who say they are very dissatisfied with their neighbourhood.
[11] It is *not* one of the characteristics used to model the dissatisfaction variable.
[12] Where area is defined as the postcode district.

home-owners and social tenants jointly. Estimation within localised geographical groups ensures exogeneity of the instruments. Estimates from the 1994 to 1998 Survey of English Housing show that mean incomes of neighbouring social tenants and property owners are uncorrelated within Local Authority areas. The coefficient in a regression of ward mean social tenant incomes on owner occupier incomes is 0.018 (s.e. 0.018). Incomes of private tenants and property owners are moderately but significantly correlated with a regression coefficient of 0.36 (s.e. 0.064). A further check is available using data on new household mortgages in the Survey of Mortgage Lenders data. Regressing the log of income (on which the mortgage is based) on the proportion in social housing, with local education and county controls, gives us coefficients of –0.135 (0.142) in the North, 0.140 (1.132) in the South East and East, and 0.138 (0.309) in the South West and West. The statistical insignificance of the coefficients is clear indication that the intrument and home-purchaser incomes are conditionally uncorrelated.

All the IV models include a Chi-squared test (Sargan test) of model specification and the validity of the overidentifying restrictions.

6.1.4. Changes between 1991 and 1995

Complete data on postcode-sector property prices is only available from the Land Registry since 1995. The census data on tenancy groups and local qualifications dates from 1991. Estimates of a property price model using 1995 prices on 1991 area characteristics will be biased if there have been substantial changes in area characteristics since 1991. Clearly, if the postcode-sector proportion highly qualified in 1995 is a multiple of the 1991 value, then we need to adjust the coefficient on the 1991 proportion downwards, though *elasticities* will be unchanged. However, changes in the distribution of education across postcode sectors will result in attenuation of regression coefficients and estimated elasticities. Comparing 1991 and 2000 deprivation indices at ward level, suggests that the attenuation due to distributional changes is probably in the order of 8% – see Appendix B for details of this calculation.

6.2 Implicit price of neighbourhood educational status

6.2.1. Postcode sector data

Table 2 to Table 4 presents the central estimates from the smoothed-spatial effects estimators, by three broad geographic regions. In each table, column 1 presents a basic OLS regression of log mean property prices in postcode-sector-dwelling-type cells in 1995, on the proportion of highly qualified adults in the postcode sector in 1991, dwelling type dummies, mean rooms in owner-occupied housing. Column 2 adds controls for ethnic composition and the density of purpose built flats. Columns 3 to 6 show estimated parameters and standard errors from the smoothed-spatial effects estimator. In column 4 and column 6 the postcode sector proportion with high qualifications is instrumented. Instruments are the proportion of households in social housing (council and local authority tenants) and the proportion of these social tenants from Indian, Pakistani and Bangladeshi ethnic groups. All the tables show estimated coefficients and standard errors[13].

To illustrate our empirical method, Figure 1 and Figure 2 show the raw and smoothed proportion with higher education qualifications in the London area. Figure 2

[13] Standard errors for the smooth spatial effect models were checked against bootstrap standard errors for a London sub-sample. For a coefficient of 1.398 the standard error was 0.313 or 0.327 when bootstrapped (100 repetitions).

illustrates the function $m(x_i \mid \mathbf{c}, b)$ in (7). Estimation is based on deviations of the raw proportion higher-educated from this surface.

The OLS estimates in columns 1 and 2 in Table 2 illustrate the partial correlations between property prices and the regressors in the South and East of England. Property prices are around 4% higher for each 1% absolute shift in the postcode sectors proportion highly qualified. But, these numbers should not be interpreted as structural parameter estimates in a model of property price determination. Differences within the region in labour market returns to skills and employment opportunities will simultaneously determine property prices and educational composition. When we introduce controls for ethnic composition and the density of purpose built flats in column 2, these attract positive and significant coefficients. Both variables proxy for central London and suburban areas, where property prices are high due to the high demand for skilled labour in the Capital.

As soon as we estimate on deviations from local means using the semi-parametric SSE model, the coefficient on highly qualified residents falls dramatically, to 1.22 (0.14) in column 3. Taking out the mean differences between localities removes biases in the estimate of the implicit price introduced by local labour market driven property price and educational composition simultaneity. The IV estimate in column 4 is only slightly below this at 1.119 (0.218). This is a somewhat surprising result, because any unobserved differences between neighbouring postcode sectors in the mean physical characteristics of housing should generate variation in mean property prices, and, we might expect, variation in the mean education and incomes of purchasers of these properties. The similarity implies that this source of endogeneity is not a serious problem. Either there is little variation in the price-related characteristics of housing in closely associated neighbourhoods, or these differences in price are not sufficient to generate differences in mean education between neighbouring postcode sectors. The variation in neighbourhood education is exogenous, even before we use the instruments. Measurement error in the educational status variable may be another factor that leads to higher IV estimates than expected relative to the OLS estimates. The educational status variable is taken from the 10% sample of the Census, so the sampling variance is high[14]. The variables used as instruments come from the 100% sample.

Columns 5 and 6 introduce controls for ethnic composition and flat density. It seems possible that neighbourhood educational variation, or variation in social housing captures variation in the physical environment which are consumption goods to property buyers. Property owners may prefer to live away from council estates because they find high rise flats and large estates unattractive. Inclusion of the density of purpose built flats (in 100s per km^2) in the postcode sector tests for this. Although this variable was significant in the raw OLS regressions, it is completely insignificant in the SSE or SSEIV models. Another consideration is the effect of ethnic minorities on property values, when there is racial prejudice amongst property owners. Ethnic background is associated with educational attainment, so sensitivity of property values to ethnic composition will affect our estimated coefficient on educational status. When the proportion of black, and Indian ethnic groups is included as a regressor in the SSE model (column 5), we find a slight fall (around 10%) in the parameter of interest. In the SSEIV model, however, we find no change. Potentially, we require the inclusion of this ethnic group control to justify our overidentifying restrictions. The proportion of social tenants in Indian sub-continent ethnic groups will not necessarily be a good instrument unconditional on ethnic overall ethnic composition (either because of prejudice, or because the proportion from ethnic minorities is correlated with mean home-owner incomes). As it

[14] Comparison of 10% and 100% sample unemployment rates suggests that 20% of the variance of the 10% sample is sampling noise.

turns out, the instruments and model pass the test, whether or not ethnic composition is included as a main regressor, though the χ^2 statistic moves in the expected direction. Perhaps the most convincing test of the validity of the instruments is the insensitivity of the IV estimate to the inclusion of ethnic group and flat density controls.

Table 3 shows the estimates for the North of England regional group. Here we see much less movement in the parameter estimates as we change from OLS on the entire region (columns 1 and 2), to the SSE models. The coefficient on educational composition falls as expected, but by nothing like the same amount as in our East and South East sub-sample estimates. In the East and South East group, it is probably the high demand for higher-educated workers and high property prices in the Capital city, relative to outlying areas, which generates the high coefficients in Table 2, column 1. In the North, local labour demand factors are less important. Nevertheless, the point estimates fall by around 20% once we abstract from local area effects. Instrumenting the proportion higher-educated *increases* the coefficient estimates, an effect which can only be attributable to the sampling noise in the regressor, but the difference between the SSEIV and SSE estimates of the key parameter is not significant in a Hausman test ($\chi^2_{(1)} = 0.654$) for column 5 versus column 6). The final estimates of our main coefficient are almost double those obtained for the South and East.

Results for Wales, the West and the South West are much like those for the North. On this sample, however, we reject the null hypothesis that the overidentifying restrictions and model specification are correct (the residuals are correlated with the instrument vector). The reason for this misspecification is unclear, but is probably linked to the highly rural geography of Wales and the South West peninsula. There is evidence here and in further specification checks (see Section 0) that the IV results are untrustworthy. Given the similarity between the SSEIV and SSE model estimates in the other regions, we can reasonably assume that the non-IV estimates are acceptable here too.

Comparing the parameters across regions, an obvious point is that the response to percentage point changes in the South East and East is markedly different from the response to a percentage point change in the other regions. This is, of course, largely due to differences in mean education levels between regions. Converting the coefficients into elasticities at the sample mean we get 0.211 (0.035) for the South and South East, 0.276 (0.044) for the North, and 0.222 (0.041) for the West, SW and Wales [15] [16]. A minimum distance estimate of the elasticities is 0.237 (0.039), and we do not reject equality to the minimum distance parameter for all regions (P value =0.356).

By these estimates, a 1% relative improvement in educational status of an average neighbourhood – as measured by the proportion with higher education qualifications – is valued at around £230 in year-2000 prices. This response of prices to local education, as predicted by proximity to social housing, explains a relatively small amount of the variation in property prices within local areas. The R^2s in within-property-type-area[17] regressions suggest that around 5% of the variation in log postcode sector mean prices in the South East and East is associated with the proportion in social housing, around 8% in the North and 4.3% in Wales, West and South West.

---

[15] Treating the mean as a constant.

[16] The elasticities are even closer across regions if we constrain the elasticities to be constant within regions by estimating a double-log model: South and SE 0.214 (0.018); North 0.195 (0.013); West, South-West and Wales 0.230 (0.019). The problem with this specification is that it implies near zero property prices in areas with near zero proportions with high qualification, and is inconsistent with the evidence presented on the log-linearity of the property-price/proportion-highly-qualified regression line.

[17] Where area is defined as the spatial group represented by a 6km × 6km square.

6.2.2. Comparison with property level data

Some readers may feel uncomfortable with results based on micro-spatially aggregated data, without any controls for individual housing or owner-characteristics, despite the identification strategy employed here. Can we be sure that our neighbourhood educational status measure is not simply measuring owner-occupier wealth, which attracts a positive coefficient because of unobserved normal-good-type property or area characteristics? Ideally, to test the robustness of the results, we want to observe the incomes of home purchasers and estimate the models conditional on own household incomes[18]. As discussed in Section 4, our second property price data set from the Survey of Mortgage Lenders (SML) has property prices and the household incomes on which the mortgage is based, but no neighbourhood identifiers. Nevertheless, we can use it to estimate the relationship between prices and Local Authority educational status, for which we have identifying codes. Existence of effects at this level of aggregation cannot be taken on their own as evidence of neighbourhood effects on property prices. There could be selection into local authority areas by individuals at different points in the income distribution, due differing returns to skills in local labour markets, and local government factors such as council tax rates.

The estimates based on matched census-SML data are tabulated in Table 5, for 1997 property data. Data for Wales is hard to match, so has been excluded. The instrument for the local authority proportion higher-educated is just the proportion in social housing. The regressions include a broad set of property type interactions and household characteristics, as listed in the table notes. Looking at Table 5, and comparing with Table 2 to Table 4, we see that the OLS estimates are somewhat higher for the South East and East and the West and South West regions, but similar for the North. Instrumenting local education brings the coefficient down in the South East and East, makes little difference in the North and increases it in the South West and West, but none of these coefficients is significantly different from the OLS estimates. If we work with elasticities at the mean and calculate the minimum distance estimate from the IV coefficients across all samples and regions we get an elasticity of 0.250, with equality across regions (p-value = 0.254)[19]. The estimates using the SML data reinforce the pattern observed by comparing the OLS and SSE estimates in Table 2 to Table 4 – that selection by education into broader geographical areas is more important in the South East and East than in other areas, hence the higher coefficients in this region when we look at effects at local authority level. Overall, the coefficients estimated using property level data with own income, plus more property and household characteristics, are not inconsistent with the estimates of more localised human capital effects in the main tables.

An important point to note from Table 5 is that the IV estimates are similar whether or not we include own-incomes. This is a good indication that the social housing instrument is exogenous to home-purchaser incomes, which is what we require. The minimum distance IV estimate of the impact of educational status unconditional on incomes is 2.384 (0.413), or 2.010 (0.352) conditional on own incomes. Without IV, the corresponding parameters are 3.058 (0.274) and 2.067 (0.051).

[18] Although own incomes may be endogenous.

[19] We can also use this data to compute the local income elasticity, using within-sample estimates of local authority mean incomes. This gives coefficients which are strikingly similar to those in Table 7, with a minimum distance estimate across all samples of 0.511 (p-value of test for equality = 0.223). The drawback is that the incomes are based on those of new owner-occupiers, not the population.

6.3 Sensitivity to bandwidth choice

Since we have no prior information on the 'best' bandwidth to use to define the local area groups in the SSE and SSEIV models, we need to check how the parameters vary with bandwidth choice. We should be worried if the estimates change dramatically for small changes in bandwidth, as this would invalidate the claim that this uncovers the parameters of a model of property price determination operating at the household level. In principle, an optimal bandwidth could be chosen based on a loss function which makes a compromise between bias and efficiency – as the bandwidth increases, efficiency increases but at the risk of biased parameter estimates. A slightly more ad-hoc approach is to re-estimate the models at intervals above and below the 3400 household bandwidth used in the main tables. The results of this exercise are in Table 6.

In all regional groups, the SSE estimates (without instruments) decrease steadily as bandwidth is reduced from 5100 to 850 households. This is to be expected, as sampling error in the 10% census sample leads to increasing attenuation in the estimated coefficients as we remove across-space variation (just as fixed effect estimation in panel data exacerbates downward bias due to measurement error). By contrast, for the South East and East, and North regional groups the SSEIV estimates are remarkably stable. The IV estimate for the South East and East increases by only 8.5%, and the estimate for the North increases by only 15% as we increase the bandwidth by a factor of 6. Hausman tests of the difference between pairs of estimates computed at different bandwidths all fail to reject the null of equality. For Wales, West and South West of England, the IV estimates are not stable across different bandwidth choices and the Sargan test statistics suggest a misspecification. The non-IV estimates are, however, relatively insensitive to changes in bandwidth around 3400 households, and are consistent with the elasticities calculated for the other regions, so I take these as the preferred estimates for this region.

6.4 Non-linearities in response

The estimates presented in Section 0 assume a linear relationship between the proportion of residents highly qualified and log mean property prices. Figure 3 shows the result of estimating the semi-parametric model of Section 5.3 on the regional groups. It is fairly clear that, apart from a few local irregularities, the relationship between the natural log of property prices and the generated neighbourhood proportion with higher education is linear, with no threshold effects[20]. Nothing here indicates that people are willing to pay proportionally more as educational status increases, though of course, the absolute amount paid increases with each one percentage point shift in educational status. In the South East and East region, a one percentage point improvement in educational status at the 75th percentile (21% higher educated) would be worth around £1600, whereas a similar relative improvement at the 25th percentile (11%) would be worth around £1300 (in 1995 prices). Some specification checks for this model are presented in Appendix C.

6.5 Implicit price of neighbourhood mean incomes

It follows from this evidence that home-owners are prepared to pay a premium to live in a highly educated neighbourhood, that we should find evidence of a premium to high income

[20] Similar results are obtained if we estimate a kernel regression of log-property type on the proportion higher-educated, where the variables are in deviations from the property-type-location means, and where location is defined by a 6km $\times$ 6km grid.

neighbourhoods, unconditional on education levels. Table 7 confirms this prediction. The specifications in the columns of these tables are identical to those in the last two columns of Table 2 to Table 4, but with log mean postcode sector incomes replacing the proportion with higher education qualifications as a regressor. Controlling for spatial variation is important. The estimates from the smooth spatial effects models are substantially lower than the OLS estimates without area controls (not shown). Except in the North, instrumenting local incomes with the proportion in social housing and proportion of social tenants from Indian ethnic groups makes little difference to the estimates. Moreover, introducing the ethnicity and flat density variables as regressors reduces the estimated elasticity only slightly. The final estimates are statistically identical across regions. The minimum distance estimate is 0.519 (0.054) and we do not reject equality of all parameters to the minimum distance estimate (*p*-value = 0.384). Households in all regions pay around 0.5% for each 1% improvement in mean neighbourhood incomes.

6.6 Comparing local income and education effects

Can we determine whether income or education is more valued in the neighbourhood social environment? Education might be important if residents seek out the productive externalities in human capital formation; if income is more important, we might emphasise considerations such as lower crime rates and a well maintained physical environment. However, disentangling the influences of family income and education on attainments is difficult, even using micro-data at the individual or household level. The problem is exacerbated in our micro-spatially aggregated data by the fact that mean incomes and education are highly correlated[21], they are measured in different periods, the income data is partly modelled, our education data is based on 10% census samples, and because both are endogenous to property prices.

Firstly, what stands out from these tables, is that the elasticities with respect to income are more than double those on education at average education levels. However, these values are very low relative to what we would expect if incomes were the principle object of preference. We can see this from conventional estimates of the returns to education in the mid to late 1990s, which are around 0.3 for higher education qualifications[22]. Since we have the property price-local income equation:

$$\ln P_i = \beta \ln y_i + \varepsilon_i \tag{17}$$

and an earnings equation:

$$\ln y_i = \delta x_i + v_i \tag{18}$$

then, if highly educated residents in the neighbourhood only effect property prices through neighbourhood incomes, we can substitute (18) into (17) to get a coefficient of $\beta\delta$ on the proportion higher educated in a property price equation. Our estimate of β is 0.51 and, assuming most household income is earnings, we know δ is around 0.3, so the coefficient on the proportion higher educated in the property price equation would be around 0.15. Our

[21] And the raw correlation between incomes and education is 0.72.
[22] e.g. Harkness and Machin (1999).

actual estimates are ten-times this figure![23]. It seems likely on this evidence, that education is valued as a local commodity for other reasons than just its impact on incomes. Mean neighbourhood income on its own acts as noisy proxy for the underlying educational status of the area.

Table 8 shows this more directly. The table shows within-postcode-district IV estimates from 1996 property value models 1996 neighbourhood incomes and 1991 education on the right hand side. The implied educational elasticity is 0.31, the income elasticity is 0.56 – slightly higher than our baseline results, due to the use of less accurate area fixed effects. Instrumenting both local education and local incomes increases the coefficient on education slightly, but the estimated income effect becomes near-zero, negative and insignificant. This is despite the fact that the instruments are more strongly correlated with incomes than education. This is clear evidence that neighbourhood education levels dominate neighbourhood incomes in the preferences of home-buyers. This is consistent with the hypothesis that an educated neighbourhood offers real social and economic benefits to its residents.

6.7 Unobserved neighbourhood heterogeneity

The models presented in the main tables use relatively few right hand side controls, and rely on the spatial effects and instruments to achieve identification. As discussed in 2.2, unobserved neighbourhood heterogeneity will compromise the interpretation of the estimates as measures of willingness to pay for marginal improvements in the neighbourhood, or as estimates of the marginal social benefits to education. We can, of course, just include more neighbourhood characteristics and observe what happens to the estimated coefficient on the proportion higher-educated. [24]

Table 9 presents results from this exercise for 1996. Neighbourhood characteristics are derived from the Census. Additional controls are primary school performance as measured in the spring of 1996 plus postcode unemployment per household in 1996. The table shows coefficients on neighbourhood education or income from separate regressions.

Row A shows the baseline model, comparable to the results in the main tables, Table 2 to Table 7. The results using postcode district fixed effects are 15 to 20% higher than those obtained using the semi-parametric model in the main tables. The results in the table are discussed below. Section 6.7.4 discusses further results based on property crime rates from a small sub-sample of postcode districts derived from the British Crime Survey in 1992.

6.7.1. The supply of owner-occupied and social housing

Negative correlation may exist between property prices and social housing if social housing was, historically, built in areas where land prices were low, and where there is strong serial correlation in land prices. Row B of Table 9 includes the proportion of households in social housing recorded in the 1981 census as an additional regressor, for those postcode sectors where at least five enumeration districts match up with enumeration districts in 1991. The

[23] If we work with years of post compulsory education an parameterise δ at 0.07 (from the Family Expenditure Survey) we find that our estimates are more than five-times higher than expected if incomes alone matter.

[24] Some of these additional characteristics may be endogenous. Consistent estimation of the parameter of interest relies on the assumption that conditioning on the vector of neighbourhood attributes is sufficient to make the unobserved determinants of property prices independent of local education levels. This is reasonable, since the OLS estimates based on within-local-area variation were close to the IV estimates in the main tables, even without additional observable neighbourhood attributes.

1991 proportion in social housing instruments neighbourhood education, or income. Since the vast majority of social housing was built prior to 1981, if the historical supply of social housing is influencing our results, we would expect the coefficient on the proportion of social housing in 1981 to be significant, and for the coefficient on educational or income status to fall. In fact, the coefficient on the 1981 proportion in social housing is insignificant, and the IV estimates are not significantly different from those in row A using the standard Hausman test.

This procedure also checks effects of social housing on the pre-1981 supply of dwellings for owner occupation. If property developers sited lower quality developments near areas of social housing, or were more likely to convert houses into flats in neighbourhoods close to social housing, or less likely to upgrade dwellings, then the coefficient on neighbourhood education may be biased upwards by unobserved differences in housing size or quality. Controlling for the 1981 proportion in social housing shows that this is not a serious consideration, for properties built before 1981 at least – it is the subsequent measure of educational status that is important. A further test for effects from the supply of flats from converted properties is to re-estimate the models excluding property transactions on flats. The new coefficients in the area reported at the foot of Table 2 to Table 4. Excluding flats increases the coefficients slightly, though not significantly so. Again we would conclude that the relationship between local education levels and property prices is not attributable to unobserved variation across neighbourhoods in the quality of housing supplied.

An important point to note here is that deterioration in the quality of housing occurring as a result of the negative externality from low human capital neighbourhoods – for example as poorer home-owners move into the area – does not result in upward-biased estimates of the implicit price. Instead, if the supply of housing measured in quality units falls back in response to falling demand, then the estimated implicit price, conditional on housing characteristics, will *under-estimate* the impact of the externality. What we want to measure is the full derivative of prices with respect to local human capital, including the effect on price resulting from property deterioration.

6.7.2. Other environmental and adult characteristics

We can gauge the extent of the importance of unobserved neighbour heterogeneity by introducing more neighbour attributes in the regressions. Row B includes some more controls – proportions unemployed, the long-term sick, and lone parents – to proxy the type of individual typically housed in social accommodation. These are frequently used as indicators of area deprivation. These three characteristics 'explain' around 75% of the variance in the proportion of social tenants, and nearly 40% of the variation in the proportion higher-educated. Additional regressors are the proportion of residents not at their current address one year earlier, the proportion of agricultural workers, the proportion over 65, and household density. Controlling for these characteristics brings down the estimated impact of local education and incomes, but the elasticities are now almost identical to those obtained using the semi-parametric spatial fixed effect models in the main tables. Although unreported in the table, it is worth noting that the coefficients on other neighbourhood characteristics have t-statistics which are less than half those on education and incomes. Elasticities on the proportions of lone parents, long-term sick and unemployed are all well below 0.1 (in absolute value) at the mean.

6.7.3. Local schools

In Gibbons and Machin (2001) we report strong local property price effects from primary school performance, as measured by National Curriculum Key Stage 2 test results at age 11, whilst secondary school has no measurable effect at postcode sector level. Row C in Table 9 includes the postcode sector mean primary school test results (the proportion achieving level 4 in the tests), plus the proportion of children determined as having special educational needs, or with local education authority statements of special needs. Although these are significant in the regressions, the coefficient on the proportion of higher-educated adults or on local incomes hardly moves. This suggests that if more highly educated neighbourhoods matter to home-owners because of their concern for the human capital accumulation of children, then the anticipated input into human capital is operating outside the primary schooling environment.

6.7.4. Local crime rates

Good local crime rate data is not easily available in the UK. A crude measure of neighbourhood crime can be constructed from the 1992 British Crime Survey, which includes 575 postcode sector identifiers. The sample size within postcode sectors is small – the mean is 21 respondents – and there are only 67 postcode districts with more than one postcode sector. A crime rate proxy – constructed as the mean number of property crimes in the last year recorded per respondent in each postcode district – attracts a negative and significant coefficient (–0.014, s.e =.007) when entered on its own in a postcode district level property value model. However, the coefficient becomes near-zero and insignificant (-0.004, s.e. 0.006) once we control for postcode district education levels. Again, we must conclude that local educational status is the more important factor.

6.7.5 Social tenant-specific effects

We can check if it is something particular about social tenants, or properties near social housing which generates the observed education-price relationship using an alternative instrument – the location of higher education institutions, which generate high education enclaves. This is a weak instrument (t-statistic of 1.67 in the prediction equations), and only 1.5% of the sample sectors have higher education institutions located within them. Nevertheless the point estimate of the education effect is almost identical to the national average effect implied by the main results. The IV coefficient is not, however, very significant (t statistic =1.29). Still, this indicates that we are picking up education related effects in our main results, rather than pure prejudice against social tenants.

6.8 Evidence for human capital externalities

As pointed out in Section 3, one prediction from a model where neighbourhood educational status generates an externality in the production of children's human capital, is that the implicit price of improvements in neighbourhood educational composition must be increasing in family size (treating family size as exogenous). We should find that the implicit price of educational status is higher in neighbourhoods with more children per household, or with a higher proportion of households with children. By interacting neighbourhood educational composition with an above/below median family size indicator in a within-postcode district property price model, we find that that the implicit price of neighbourhood educational status is 1.845 (s.e. 0.128) in below-median family size sectors, but 2.225 (0.063) in above-median family size sector. The difference is significant (t = 2.66). This is consistent with the hypothesis that households value good neighbourhoods because of the benefits to children, though there is no direct evidence here that these benefits accrue in terms of children's educational attainments, or acquisition of other productive skills.

The proportion of home-owners with children is also increasing in the proportion of highly qualified residents – once this is instrumented by the proportion of social tenants in the neighbourhood. Again this suggests that families with children benefit more from good neighbourhoods, and that they are more willing than others to bid up property prices in high-education neighbourhoods. Regressing the postcode sector proportion of home-owners with children on the proportion of residents with diplomas and degrees (where these variables are in deviations from postcode district means) gives an insignificant coefficient of 0.006 (s.e. = 0.025). Instrumenting the proportion with high qualifications with the proportion in social housing drives the coefficient up to 0.148 (0.026). A reduction on the proportion of social tenants equivalent to a one percentage point rise in the proportion of residents with diplomas and degrees is associated with a 0.14% rise in the proportion of home owners with children (from a mean of 30%). One interpretation of this is that home-owners with children are willing to bid more for marginal improvements in the educational status of neighbourhoods because of the impact on the educational attainments of their children. The relationship is not evident in the OLS relationship, because low home-owner household incomes are associated with larger family size, which obscures the relationship of interest.

7. Concluding Remarks

These results demonstrate that neighbourhood property prices respond to exogenous variation in neighbourhood education levels and local incomes generated by variation in the local proportion in social housing. Households value residence in 'educationally rich' and higher-income neighbourhoods. The estimated elasticities in the average neighbourhood are stable across regions, at around 0.24 for the proportion higher-educated, and 0.52 for mean incomes – unconditional on education. A semi-parametric, within-area, IV approach identifies these effects. We get similar elasticities on local authority educational status using property-level micro-data and conditioning on home-purchaser incomes. Our local income elasticity is of the same order as the estimates buried in hedonic regressions in the US literature (around 0.35-0.41).

Educational differences between neighbourhoods seem far more important than incomes – the coefficient on local human capital is much higher than expected if income alone mattered, and the income coefficient vanishes once we include education and income together in the IV regressions. Using additional Census, school, unemployment and crime data, we can see that the sensitivity of prices to local educational status is undiminished once we abstract from other observable characteristics of individuals in the neighbourhood. We conclude that households place particular importance on the educational status of a neighbourhood in choosing a residential location, and that households with more children seem prepared to pay more. This highlights the potential importance of community spillovers in the production of human capital. These results have direct relevance to the cost-benefit analysis of measures to improve the educational status of deprived neighbourhoods, as well as to educational policy in general. Unfortunately, without detailed information on neighbourhood educational attainments other than higher education qualifications, we can make no assessment of the extent to which higher education matters over and above education in general.

On the assumption that it is the educational status of communities that matters to households, we can make a tentative assessment of the long-run social, community-level benefits of education and compare this with the private returns. I focus on households headed by someone under the age of forty[25]. Mean household annual earnings for these households was around £19000, and the mean property price was £65000 in 1995. A 10% relative increase in the proportion of adults with higher education qualifications in 1995 would have meant a 1.9% absolute increase in the proportion with higher-education qualifications. Assuming the private returns to higher education qualifications are in the order of 25% to 30%, this improvement in education implies an increase in mean earnings of around 0.53%, or £100 on average household income. From the estimates presented in this paper, this change in educational attainments would be valued at £1500 at the 1995 mean property price. Average mortgage interest rates in 1995 were around 7% and the mean loan period 22.5 years, so £1500 is equivalent to £130 per annum in mortgage payments. By this calculation, the money-metric value of the non-pecuniary benefits to society from an individual gaining higher qualification is *higher* than the mean return in terms of increased earnings. Note, this figure is based on changes to the proportion higher-educated only. If we assume that the proportion in all post-school attainment groups increases in proportion to the proportion with higher education qualifications, then a 10% relative improvement represents a 10% increase in the mean number of years of post-school education. Taking a generous estimate of the returns to years of schooling as 0.07, this relative increase in mean non-compulsory years of education (1.3 years for 25 to 40-year-olds) in 1995, gives a return per household of £170. Again, this is similar to our value on the pure community benefits.

If we believe that households value community educational status purely as an input into children's human capital accumulation, and that parents can transfer income directly to children, it follows that the average household, which has one child, expects a 10% relative improvement in quality of the average neighbourhood to increase a child's expected household income by around 0.7%[26]. We can take this is an upper bound to the average impact of neighbourhood quality on a child's future household income. If all improvements in income are linked to better individual educational attainments, and returns to education are expected to remain unchanged, then parents expect this 10% relative change in neighbourhood status to improve their child's chances of gaining higher education qualifications by a similar proportional amount[27]. This unit elasticity is substantially higher than the child outcome-neighbourhood educational elasticities estimated in the neighbourhood effects literature, which are in the order of 0.1-0.2 (see Kremer, 1997 or Gibbons, 2001). Clearly, not all the expected benefits of a better neighbourhood relate to

[25] Sources of the figures that follow are variously: Family Resources Survey 1995/6, Survey of English Housing 1995, Survey of Mortgage Lenders 1995. Age 40 is the 75th percentile in the age distribution of those taking out mortgages in the survey of mortage lenders. Returns to education control for gender, ability and family background – calculations from National Child Development Survey and 1970 British Cohort Survey, but see also Blundell, Dearden, et al. (2000), or Harkness and Machin (1999). Mortgage interest rates in 1995 were 6.15% according to the 5% Survey of Mortgage Lenders, though the figure given in Building and Construction Statistics is 7.83% per annum. Returns to years of education is the figure from a simple regression of log earnings on age left full time education, age, age squared and gender for individuals aged 25-40 between 1992 and 1996 in the Family Expenditure Survey.

[26] The mean number of children per owner-occupier household for owner occupiers headed by someone under 40 in the Survey of English Housing in 1995 is one. The calculation assumes that expected child's household income is the same as current mean household income, so we just divide the value of the benefits (£130) by household income.

[27] Because the change in the proportion of people with higher qualifications necessary to increase earnings by 0.7% is roughly 2.3%, assuming the return to higher qualifications is around 0.3. The current proportion with higher qualifications is tending towards 23%.

better earnings-related outcomes for children, or else the existing literature mis-measures this effect.

These back-of-an-envelope calculations are, of course, approximate. Still, the message comes across that the residents are prepared to pay for neighbourhoods with higher stocks of human capital, and that the aggregate non-earnings related community benefits per household are of a similar order to the aggregate private returns per household as measured by the increment to earnings from higher education qualifications. It should be borne in mind also that the social benefits measured here are only those that accrue locally, so will not include spillovers in production, in workplace relations, in technological innovation and in other areas where action is at a broader geographical level. Given the size of these effects measured here, these community benefits warrant further analysis. Focussing on the private returns to education seriously understates the value of education to society, and any policy decisions based on these returns alone may result in sub-optimal provision of educational services.

Table 1: Summary statistics for local incomes, education and property prices

	South East and East		North of England		Wales, S-West & West	
	Mean/s.d	Min/Max	Mean/s.d	Min/Max	Mean/s.d.	Min/max
1995 sector mean	80435	10916	49245	10714	57168	13333
price	(50139)	776000	(22901)	250875	(25931)	375500
1996 sector mean	83758	14678	50359	12333	58900	12916
price	(52570)	716666	(23786)	246000	(26630)	279417
1999 sector mean	120296	16562	62647	12385	78850	14916
price	(74843)	834025	(33452)	322172	(40135)	407821
Mean annual	131	3	92	3	99	3
sector sales	(74)	584	(59)	461	(65)	652
volume						
Mean sector	147481	31347	93135	23333	104880	23779
detached price	(74958)	834025	(31363)	322172	(36955)	407821
Mean sector semi-	91150	27330	51549	12987	58818	16550
detached price	(56517)	820825	(13868)	218525	(18354)	299357
Mean sector	83081	21074	36725	12385	54178	15937
terraced price	(59889)	792500	(12875)	227000	(18417)	220500
Mean sector	69881	10916	42509	10714	50489	12916
flat/mais. price	(50438)	538693	(18379)	263313	(24433)	292750
Mean postcode	2965	-	2858	-	1991	-
sectors						
Proportion with	0.167	0.000	0.123	0.000	0.133	0.000
diplomas, degrees	(0.081)	0.750	(0.077)	0.680	(0.064)	0.480
Proportion in	0.197	0.000	0.244	0.000	0.191	0.000
social housing	(0.147)	0.873	(0.178)	0.957	(0.128)	0.832
1996 sector mean	22714	10520	17864	8900	18081	10180
income	(4486)	47020	(3913)	39210	(3399)	39430
1996 postcode	2778	-	2766	-	1883	-
sectors						
1999 sector mean	24512	11120	19413	8150	19795	10360
income	(5224)	49490	(4359)	41230	(3779)	33670
1999 postcode	2822	-	2794	-	1941	-
sectors						

Means of property prices are means of postcode sector means, weighted by sales volumes.

Means of qualifications and social housing weighted by households.

Means of incomes are means of postcode sector means, weighted by number of households.

Table 2: Property price response to neighbourhood educational composition, South East and East England, 1995

	OLS	OLS	OLS-SSE	IV-SSE	OLS-SSE	IV-SSE	Mean
Proportion highly qualified in 1991	4.259 (0.089)	3.663 (0.083)	1.218 (0.139)	1.119 (0.218)	1.152 (0.143)	1.119 (0.209)	0.168
Density of purpose built flats (100s/km^2)	-	9.0 e^{-3} (0.9 e^{-3})	-	-	0.2 e^{-3} (0.8 e^{-3})	0.2 e^{-3} (0.8 e^{-3})	7.538
Proportion Black, Indian, P'stan, B'desh	-	0.269 (0.077)	-	-	-0.973 (0.184)	-0.979 (0.189)	0.041
Mean rooms in owner-occupied housing	-0.146 (0.011)	0.020 (0.013)	0.212 (0.015)	0.217 (0.015)	0.208 (0.015)	0.209 (0.015)	5.495
Detached	0.456 (0.006)	0.463 (0.005)	0.471 (0.005)	0.471 (0.005)	0.470 (0.005)	0.470 (0.005)	0.272
Flat/Maisonette	-0.523 (0.006)	-0.537 (0.006)	-0.563 (0.005)	-0.563 (0.005)	-0.563 (0.005)	-0.563 (0.005)	0.231
Terraced	-0.164 (0.005)	0.176 (0.004)	-0.175 (0.004)	-0.175 (0.004)	-0.175 (0.004)	-0.175 (0.004)	0.272
Constant	11.333 (0.055)	10.447 (0.071)	-	-	-	-	-
Overall R2	0.685	0.725	0.925	0.925	0.925	0.925	-
Within R2	-	-	0.844	0.844	0.845	0.844	-
P-value test of restrictions	-	-	-	0.110	-	0.840	-

Dependent variable is log of postcode sector mean property-type price.

Sample size (sectors x property type) = 9431.

Min, mean, max bandwidth: .24 km, 1.27 km, 8.75 km.

Mean house price = £85437.

Mean of dependent variable (log-mean-price) = 11.19.

Mean Eastings 52854, Northings 18343.

Instruments in columns 4 & 6 are postcode-sector proportion in social housing and proportion of social housing tenants from Indian, Pakistani, and Bangladeshi ethnic groups.

Estimate of educational composition parameter is 1.192 (0.222) in column 4 if social housing is the only instrument.

Excluding transactions on Flats and Maisonettes from sample gives estimate of educational composition parameter of 1.262 (0.200) in column 6.

Table 3: Property price response to neighbourhood educational composition, North of England, 1995

	OLS	OLS	OLS-SSE	IV-SSE	OLS-SSE	IV-SSE	Mean
Proportion highly qualified in 1991	2.468 (0.064)	2.472 (0.064)	1.969 (0.175)	2.290 (0.321)	1.924 (0.170)	2.163 (0.341)	0.128
Density of purpose built flats (100s/km^2)	-	1.6 e^{-3} (0.7 e^{-3})	-	-	-1.4 e^{-3} (1.5 e^{-3})	-1.2 e^{-3} (1.5 e^{-3})	2.714
Proportion Black, Indian, P'stan, B'desh	-	-0.334 (0.079)	-	-	-0.636 (0.216)	-0.577 (0.219)	0.017
Mean rooms in owner-occupied housing	0.080 (0.011)	0.081 (0.011)	0.103 (0.030)	0.074 (0.033)	0.105 (0.030)	0.086 (0.033)	5.520
Detached	0.493 (0.005)	0.483 (0.005)	0.477 (0.004)	0.477 (0.004)	0.477 (0.004)	0.477 (0.004)	0.255
Flat/Maisonette	-0.357 (0.009)	-0.359 (0.009)	-0.394 (0.009)	-0.395 (0.009)	-0.394 (0.009)	-0.394 (0.009)	0.107
Terraced	-0.262 (0.004)	0.261 (0.004)	-0.262 (0.004)	-0.262 (0.004)	-0.262 (0.004)	-0.262 (0.004)	0.316
Constant	10.009 (0.055)	10.009 (0.057)	-	-	-	-	-
Overall R2	0.782	0.783	0.892	0.892	0.892	0.892	-
Within R2	-	-	0.818	0.821	0.818	0.821	-
P-value test of restrictions	-	-	-	0.192	-	0.276	-

Dependent variable is log of postcode sector mean property-type price.

Sample size (sectors x property type) = 8081.

Min, mean, max bandwidth: .28 km, 1.44 km, 22.90 km.

Mean house price = £52554.

Mean of dependent variable (log-mean-price) = 10.77.

Mean Eastings 41272, Northings 41884.

Instruments in columns 4 & 6 are postcode-sector proportion in social housing and proportion of social housing tenants from Indian, Pakistani, and Bangladeshi ethnic groups.

Estimate of educational composition parameter is 2.253 (0.323) in column 4 if social housing is the only instrument.

Excluding transactions on Flats and Maisonettes from sample gives estimate of educational composition parameter of 2.406 (0.264) in column 6.

Table 4: Property price response to neighbourhood educational composition, Wales, West and South West of England, 1995

	OLS	OLS	OLS-SSE	IV-SSE	OLS-SSE	IV-SSE	Mean
Proportion highly qualified in 1991	2.833 (0.111)	2.663 (0.107)	1.749 (0.211)	1.757 (0.323)	1.648 (0.200)	2.024 (0.303)	0.135
Density of purpose built flats (100s/km^2)	-	14.5 e^{-3} 2.2 e^{-3}	-	-	3.5 e^{-3} 3.0 e^{-3}	5.4 e^{-3} 2.9 e^{-3}	2.252
Proportion Black, Indian, P'stan, B'desh	-	-0.368 (0.077)	-	-	-0.916 (0.162)	-0.738 (0.173)	0.020
Mean rooms in owner-occupied housing	0.017 (0.017)	0.075 (0.018)	0.167 (0.033)	0.190 (0.034)	0.181 (0.035)	0.181 (0.033)	5.566
Detached	0.460 (0.006)	0.459 (0.006)	0.456 (0.005)	0.455 (0.005)	0.455 (0.005)	0.455 (0.005)	0.278
Flat/Maisonette	-0.369 (0.009)	-0.378 (0.009)	-0.429 (0.008)	-0.431 (0.008)	-0.430 (0.008)	-0.430 (0.008)	0.142
Terraced	-0.196 (0.005)	-0.197 (0.005)	-0.192 (0.004)	-0.192 (0.034)	-0.192 (0.004)	-0.192 (0.004)	0.289
Constant	10.375 (0.089)	10.048 (0.090)	-	-	-	-	-
Overall R2	0.698	0.708	0.888	0.889	0.889	0.889	-
Within R2	-	-	0.816	0.820	0.817	0.821	-
P-value test of restrictions	-	-	-	0.000	-	0.040	-

Dependent variable is log of postcode sector mean property-type price.

Sample size (sectors x property type) = 6058.

Min, mean, max bandwidth: 0.40 km, 1.69 km, 12.57 km.

Mean house price = £58119.

Mean of dependent variable (log-mean-price) = 10.87.

Mean Eastings 34637, Northings 20930.

Instruments in columns 4 & 6 are postcode-sector proportion in social housing and proportion of social housing tenants from Indian, Pakistani, and Bangladeshi ethnic groups.

Estimate of educational composition parameter is 1.844 (0.322) in column 4 if social housing is the only instrument.

Excluding transactions on Flats and Maisonettes from sample gives estimate of educational composition parameter of 1.928 (0.308) in column 6.

Table 5: Property price response to local education: Survey of Mortgage Lenders data, by region, 1997

	South East and East		North		West and SW	
	OLS	IV	OLS	IV	OLS	IV
Local authority proportion with higher education	2.210 (0.194)	1.625 0.514)	2.050 (0.050)	1.998 (0.319)	2.502 (0.393)	3.288 (0.899)
Own log income	0.435 (0.017)	0.445 (0.018)	0.380 (0.013)	0.381 (0.013)	0.382 (0.016)	0.376 (0.017)
R^2	0.713	0.711	0.723	0.723	0.699	0.698
Sample size	11085		7110		4367	
Mean log-price	11.306		10.886		11.035	
Mean price	£95577		£61369		£70638	

Dependent variable is log of property price.

All models include: main purchaser age, number of males, number of females, bugalow, detached, semi-detached, terraced, flat/maisonette (converted), flat/maisonette (purpose built), other dwelling type, built 1919-39, 1940-60, 1961-1980, after 1980, new, number of rooms, dwelling type × number of rooms, dwelling type × property age, county dummies.

Minimum distance estimate of IV coefficient on educational status = 2.010 (0.352).
Test of equality across regions *p*-value = 0.630.

Without own-incomes as control, IV coefficients on local educational status are:

SE&E: 1.681 (0.877), North: 2.353 (0.387), West and SW: 4.008 (1.205).

Minimum distance estimate = 2.384 (0.413).
Test of equality across regions *p*-value = 0.651.

Table 6: Sensitivity of education parameter estimates to bandwidth choice

	South and East		North		West, SW and Wales	
	OLS	IV	OLS	IV	OLS	IV
850 households	0.687 (0.277)	1.082 (0.383)	1.574 (0.233)	1.968 (0.452)	1.403 (0.397)	1.197 (0.667)
Overidentification test	-	0.28	-	0.93	-	0.452
Mean bandwidth	0.64 km		0.72 km		0.85 km	
1700 households	0.926 (0.214)	1.081 (0.280)	1.818 (0.218)	2.008 (0.428)	1.633 (0.277)	1.401 (0.410)
Overidentification test	-	0.79	-	0.59	-	0.01
Mean bandwidth	0.90 km		1.02 km		1.19 km	
3400 households	1.152 (0.143)	1.119 (0.209)	1.924 (0.170)	2.163 (0.341)	1.648 (0.200)	2.024 (0.303)
Overidentification test	-	0.84	-	0.28	-	0.04
Mean bandwidth	1.27 km		1.44 km		1.69 km	
5100 households	1.244 (0.119)	1.170 (0.184)	1.954 (0.144)	2.281 (0.280)	1.677 (0.169)	2.253 (0.276)
Overidentification test	-	0.619		0.15	-	0.14
Mean bandwidth	1.56 km		1.77 km		2.08 km	
Hausman test (1700 against 850)	$\chi^2(1) = 0.00$		$\chi^2(1) = 0.075$		$\chi^2(1) = 0.74$	
Hausman test (3400 against 1700)	$\chi^2(1) =0.34$		$\chi^2(1) = 0.36$		$\chi^2(1) = 5.1$	
Hausman test (5100 against 3400)	$\chi^2(1) =0.26$		$\chi^2(1) = 0.37$		$\chi^2(1) = 3.4$	

Dependent variable is log of postcode sector mean property-type price.

Table shows estimates of coefficients in model of columns 5 an 6 in Table 2 to Table 4 under different bandwidth choices. Hausman tests are for tests of parameter equality under different bandwidth assumptions.

Table 7: Property price response to neighbourhood incomes, by region, 1996 and 1999

	South East and East		North		Wales, West and SW	
	OLS-SSE	IV-SSE	OLS-SSE	IV-SSE	OLS-SSE	IV-SSE
Log mean postcode sector incomes	0.465 (0.035)	0.487 (0.051)	0.742 (0.034)	0.531 (0.053)	0.603 (0.057)	0.556 (0.066)
Density of purpose built flats (100s/km^2)	0.2 e^{-3} (0.5 e^{-3}	0.2 e^{-3} (0.5 e^{-3}	1.8 e^{-3} (1.2 e^{-3}	0.0 e^{-3} (1.0 e^{-3}	5.6 e^{-3} (1.9 e^{-3}	6.4 e^{-3} (2.0 e^{-3})
Proportion Black, Indian, P'stan, B'desh	-1.174 (0.166)	-1.178 (0.158)	-0.659 (0.096)	-0.858 (0.162)	-0.817 (0.120)	-0.813 (0.138)
Mean rooms in owner-occupied housing	0.172 (0.012)	0.167 (0.013)	0.096 (0.018)	0.152 (0.019)	0.148 (0.029)	0.169 (0.026)
Detached	0.473 (0.003)	0.473 (0.003)	0.506 (0.003)	0.507 (0.052)	0.473 (0.004)	0.473 (0.004)
Flat/Maisonette	-0.586 (0.004)	-0.585 (0.004)	-0.405 (0.006)	-0.404 (0.006)	-0.474 (0.005)	-0.474 (0.005)
Terraced	-0.186 (0.003)	-0.186 (0.003)	-0.272 (0.003)	-0.272 (0.003)	-0.198 (0.003)	-0.198 (0.003)
Overall R2	0.940	0.940	0.898	0.898	0.913	0.913
Within R2	0.853	0.853	0.820	0.812	0.839	0.840
P-value test of restrictions	-	0.336	-	0.152	-	0.207
Sample size	19445		16241		12486	
Mean log-incomes	3.164		2.941		2.946	
Mean log-price	11.40		10.85		11.00	
Mean price	£108797		£58334		£67453	
Mean bandwidth	1.30 km		1.50 km		1.80 km	

Dependent variable is log of postcode sector mean property-type price.

Instruments in columns 4 & 6 are postcode-sector proportion in social housing and proportion of social housing tenants from Indian, Pakistani, and Bangladeshi ethnic groups.

Reducing bandwidth by factor of 2 gives estimated parameter on educational composition of:
0.415 (0.051) in column 1, 0.576 (0.082) IV in column 2 and Sargan test statistic *p*-value of 0.38.
0.761 (0.042) in column 5, 0.571 (0.071) IV in column 6, with Sargan test statistic *p*-value of 0.22.
0.525 (0.085) in column 5, 0.364 (0.099) IV in column 6 and Sargan test statistic *p*-value of 0.06.

Table 8: Comparison of education and income effects: Within-postcode-district IV estimates, all regions, 1996 property prices

Postcode sector proportion higher educated	2.100 (0.092)	-	2.163 (0.592)
Log mean postcode sector incomes	-	0.561 (0.025)	-0.017 (0.160)
Sectors × property types	25586	25586	23586

Both models include dwelling-type dummies, mean rooms in owner occupied housing, proportion non-white, purpose-built flat density, postcode district dummies.

Instruments are the proportion of social tenants, the proportion of Indian subcontinent and the proportion of blacks in social housing.

F-statistic on three instruments in income equation = 1118.87.

F-statistic on three instruments in education quation = 592.25.

Sargan test of overidentifying restrictions *p*-value = 0.240 (column 3).

Table 9: Property price response to neighbourhood: estimates with additional controls

		Education		Log incomes
		Coefficient	Elasticity	Elasticity
A	Dwelling type, year, proportion non-white, average rooms, purpose-built-flat density, postcode district fixed effects	1.852 (0.063)	0.270 (0.009)	0.574 (0.021)
	Sample size	24084	-	23550
B	Model A, plus proportion of social households in 1981: IV using 1991 proportion of social households	2.213 (0.226)	0.324 (0.033)	0.498 (0.055)
	Sample size	12171	-	12100
C	Model A, plus mid-year unemployment per household, household density per km^2, proportions in agricultural employment, one year migrants, lone parents, long-term sick, age 65 plus	1.382 (0.078)	0.202 (0.011)	0.520 (0.028)
	Sample size	24084	-	23550
D	Model C, plus primary school performance, proportion of pupils with statements and special educational needs (Wales excluded)	1.378 (0.079)	0.200 (0.012)	0.522 (0.026)
	Sample size	22180	-	22180

1. Dependent variable is log of 1996 property price
2. School data taken from DfEE 1996 Primary School Performance Tables.
3. Unemployment counts from Nomis.
4. All other controls from 1991 census.

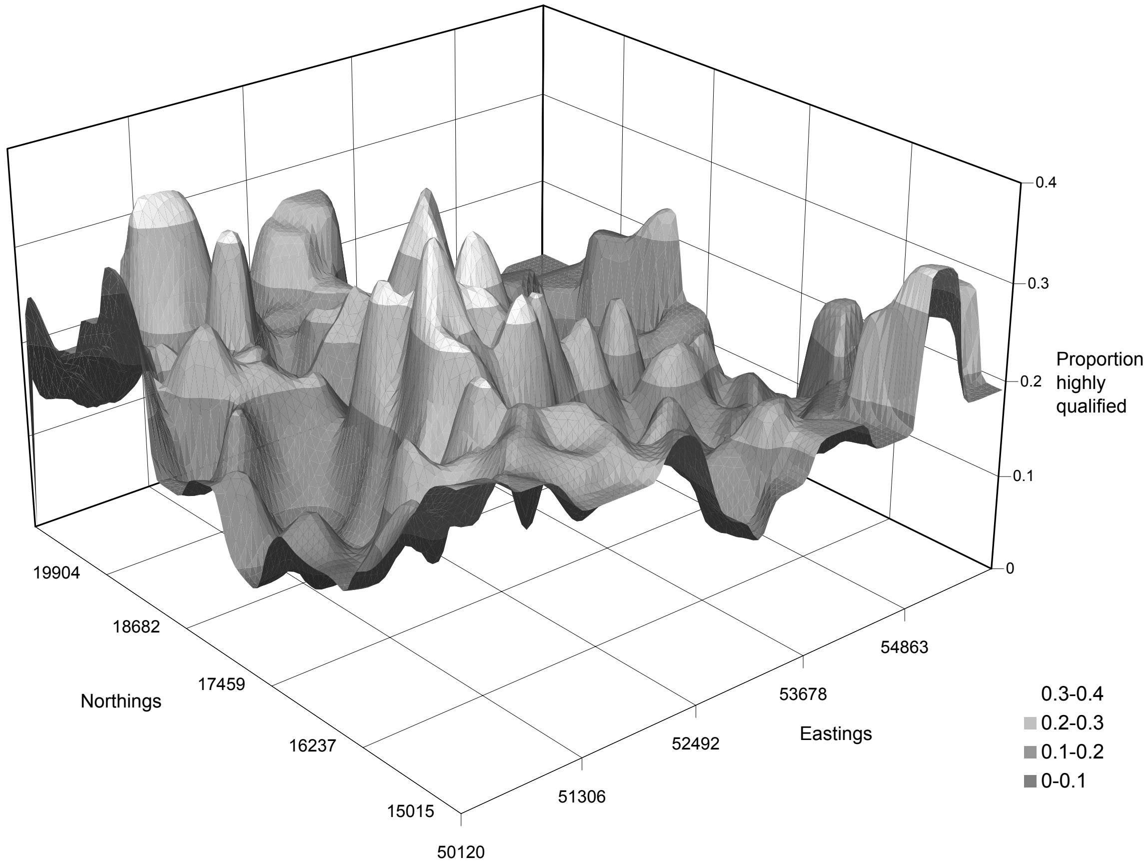
Figure 1:Raw postcode sector proportion with high qualifications, 1991: London and surrounding area

Figure shows postcode proportions with higher education qualifications in postcode sectors in London area, Eastings 50000 to 56000, Northings 15000 to 21000.

Source 1991 Census

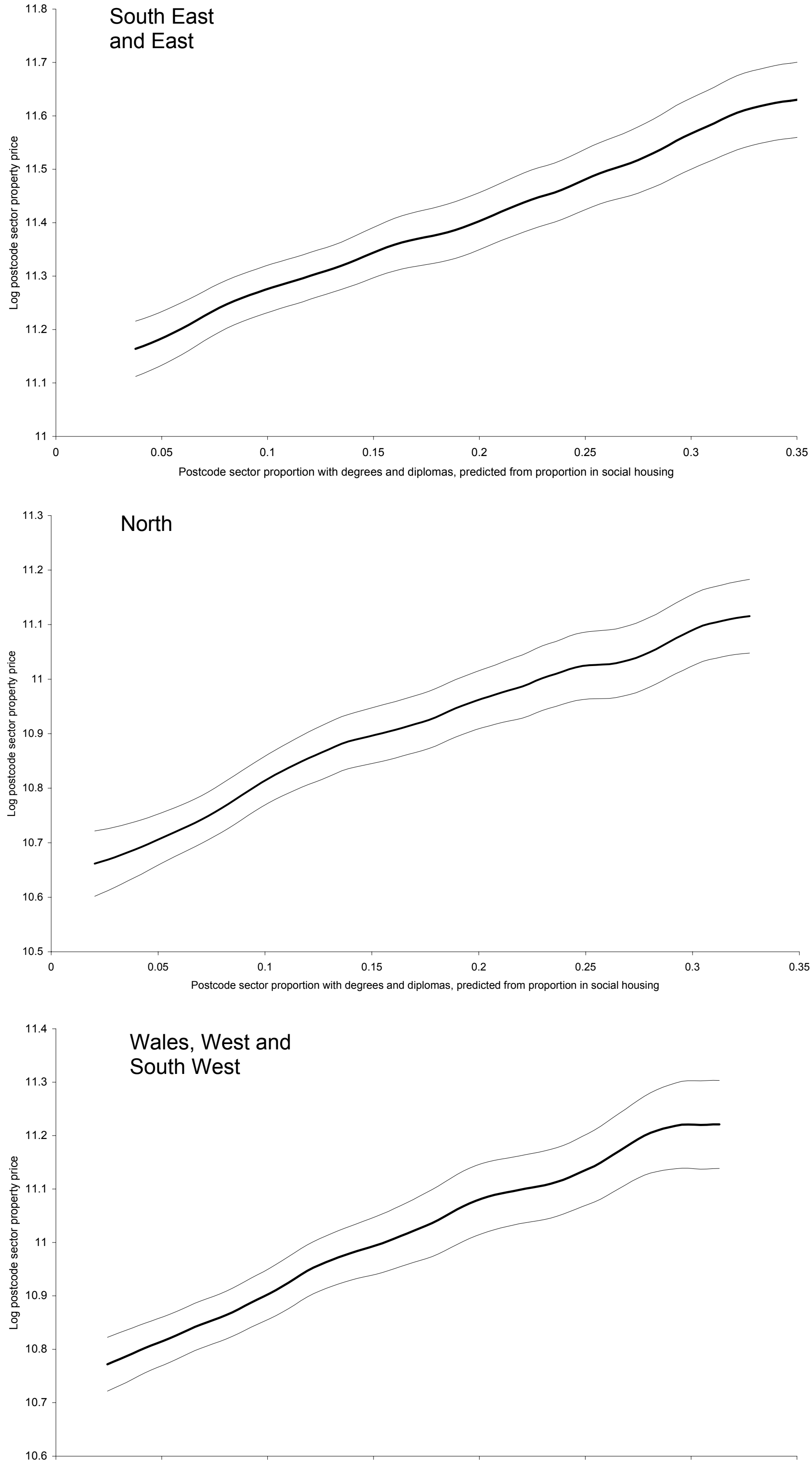
0.01-0.11
0.11-0.15
0.15-0.21
0.21-0.27
0.27-0.56

Figure 2: Smoothed postcode sector proportion with high qualifications: London and surrounding area 1991



Spatial bandwidth 1 km, Gaussian kernel
Eastings 50000 to 56000, Northings 15000 to 21000

Figure 3: Average kernel regression lines: property price on local educational composition



Spatial bandwidth 2.3km, 2.5km 3 km. Bandwidth on local education 0.0131, 0.0125, 0.0116.

8. Appendix A

The justification for using the proportion of social tenants as an instrument for neighbourhood education or incomes is that mean incomes and education levels of social tenants are unambiguously lower on average than those of owner-occupiers. We can write the proportion of any group of residents in location *i*, with qualifications q as

$$P_i(q) = P(q \mid o) + [P(q \mid s) - P(q \mid o)] \cdot P_i(s)$$

so a first-step linear regression of the proportion qualified, on the proportion in social housing gives estimates of the mean proportion of owner-occupiers with qualifications q, and the mean difference between the proportion of social tenants and owner occupiers with qualifications q. Similarly, for mean incomes

$$\bar{y}_i = \bar{y}^o + \left(\bar{y}^s - \bar{y}^o\right) \cdot P_i(s)$$

and taking logs:

$$\ln \bar{y}_i = \ln \bar{y}^o + \ln\left[1 + \frac{\left(\bar{y}^s - \bar{y}^o\right)}{\bar{y}^o} \cdot P_i(s)\right] \approx \ln \bar{y}^o + \frac{\left(\bar{y}^s - \bar{y}^o\right)}{\bar{y}^o} \cdot P_i(s)$$

9. Appendix B

9.1 Correlation between Indices of Deprivation 2000 and Census education variable

The table below gives the coefficients from a regression of the deprivation indices on the ward proportion of highly qualified residents, taken from the 1991 census.

Association of deprivation indices and standardised Census qualifications measure

	OLS	IV	Within-district	IV
Standardised educational deprivation index	-0.607 (0.009)	-1.091 (0.036)	-0.500 (0.009)	-0.823 (0.019)
Standardised employment deprivation index	-0.503 (0.010)	-	-0.370 (0.009)	-
Standardised income deprivation index	-0.557 (0.009)	-	-0.466 (0.009)	-
Standardised health deprivation index	-0.556 (0.009)	-	-0.376 (0.008)	-
Standardised housing deprivation index	-0.329 (0.011)	-	-0.356 (0.010)	-
Standardised multiple deprivation index	-0.561 (0.009)	-	-0.446 (0.009)	-

Regressor is standardised box-cox zero skewed transform of 1991 ward proportion with diplomas, degrees and above. Regression coefficient gives estimated change in standard deviations to one standard deviation change in Census education measure. Instrument is 1991 ward proportion in social housing

The variables transformed to zero-skewed, standardised normal variates so that the coefficient gives the change in the deprivation index in standard deviations associated with a one standard deviation change in educational composition as measured in 1991. The first column gives the OLS estimates, the second instruments the 10% census sample based education measure with the proportion in social housing (taken from the 100% sample) to correct for measurement error. In the third and fourth columns, the variables are transformed to give within-census district estimates. Whilst the R^2 s from the regressions are moderate (a maximum of 0.37 for the educational deprivation index), the coefficients and standard errors confirm that the census variable is a reasonable proxy for most aspects of neighbourhood deprivation, as measured by the latest data. Given that almost 10 years has passed since the last Census, we would expect only moderate correlation between current distribution of deprivation and that in 1991. However, based on the IV estimates, wards which were one standard deviation below the mean in the proportion of qualified adults are, on average, one standard deviation above the mean on the current measure of educational deprivation.

9.2 Tenancy group, ethnicity and high qualifications

The table below shows the proportions with equivalent qualifications to those measured by the 1991 census, taken from the Labour Force Survey for England and Wales. The figures are shown for 1991/92 and 1994/95.

Proportion with high qualifications: variation by tenancy group and ethnic group

	Census	LFS				
	All tenures	All tenures	Non-social	Social	Social, non-Indian subcontinent	Social, Indian, subcontinent
1991	0.147	0.150	0.175	0.027	0.027	0.052
1994/5	-	0.190	0.224	0.036	0.036	0.055

Source: Labour Force Survey and 1991 Census

In 1991, only 2.3% of tenants in social housing had higher diplomas, degrees or higher qualifications, compared to over 15% in other tenancy groups. Social tenants in the Indian ethnic groups do better, with 4.5% gaining these qualifications. The figures show that relative positions of social tenants in the educational distribution has changed little since 1991, though the total proportion in social housing has fallen by a few percent. There is nothing in these aggregate changes to suggest that the use of the proportion of social tenants in 1991 will be a bad predictor of educational levels in 1995, or incomes in 1999. Given the relatively low level of social housing construction in the early 1990s, and the fall off in council house sales we would not expect dramatic changes in the postcode sector proportions in social housing over the decade. The stock of social rented dwellings in England and Wales was 4.75 million in 1991, 4.66 million in 1995 and 4.44 in 1999. The number of households in the social rented sector in England remained relatively unchanged over the period 1991-1999. The figures are:

Households in the social rented sector: England 1991-1999

Year	Council	RSL	All
1991	3872	564	4435
1994-5	3677	767	4444
1995-6	3494	910	4404
1996-7	3482	1010	4492
1997-8	3333	987	4320
1998-9	3324	1028	4352

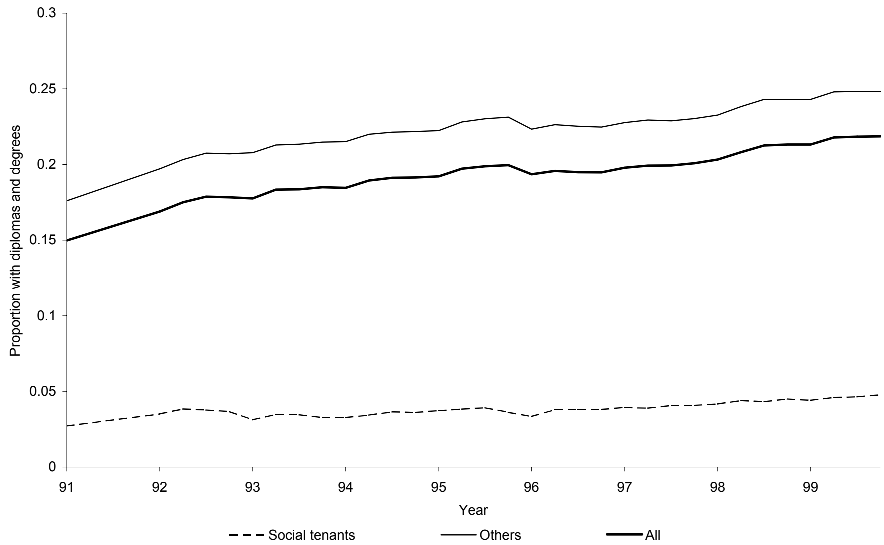
Figures are in 1000s

Source: DETR Housing and Construction Statistics, 1999

9.3 The effect of changes in educational composition

The most important relevant national changes are documented in the figure beow. These chart the growth in the proportion with high qualifications and the fall in the proportion of social tenants over the period since the last Census. The figure below shows that the proportion of social tenants with diplomas, degrees and other higher education qualifications increased from 2.7% in 1991 to 3.6 % in 1994/5- a growth of 33% – whilst the proportion of non-social tenancy groups with higher education rose from 17.5% to 22.4%. Overall there was a 27% growth in the proportion of those with high qualifications between 1991 and 1994/95.

Proportion with high qualifications (degrees, diplomas and teaching qualifications) 91-99



Source: Labour Force Survey

What are the implications of this change for estimates of the response of 1995 property prices to the spatial distribution of education levels as measured in 1991? If all neighbourhoods experienced 28% increase in the proportion with diplomas and degrees, then conversion of parameters measuring the response to 1991 education levels to measurements of the sensitivity to contemporaneous education levels is straightforward. The coefficients must be adjusted downwards by 28%, and the elasticities will be unchanged. However, changes in the distribution of education across neighbourhoods mean that estimated coefficients and elasticities will be downward biased relative to the parameters on contemporaneous education levels (the classical measurement error problem). Unfortunately there is no information on changes in the ranking and distribution of educational composition between 1991 and 1995, but we can get a feel for the scale of the problem by comparing 1991 ward level indices of deprivation and the DETR Indices of Deprivation 2000. Various composite indices are available from 1991 Census data – the Carstairs, Townsend, DoE, Jarman – though none is directly comparable to any of the 2000 indices. Nevertheless, the 2000 indices can explain up to 66% of the variance in the 1991 indices.

I assume we can write the local proportion of highly qualified persons in 1991 as a multiple of true local proportion in year t, plus an uncorrelated error term that grows with time.

$z_{0,i} = \alpha_t z_{t,i} + \varepsilon \cdot t$

A regression estimate of β in the model

$y_{t,i} = \beta \cdot z_{t,i} + \upsilon_i$

where $z_{t,i}$ is proxied by $z_{0,i}$ will give an inconsistent estimate of β:

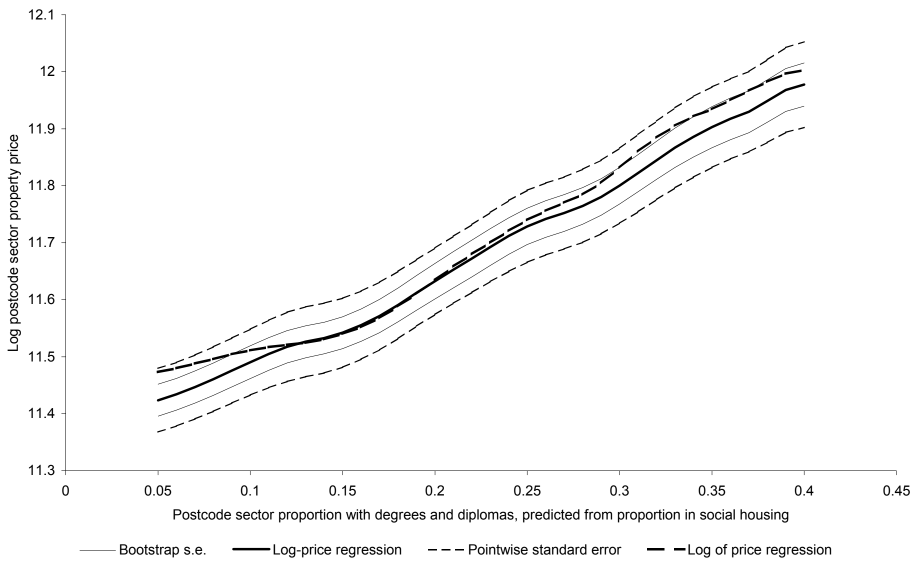
$$\text{plim}\hat{\beta} = \frac{\beta}{\alpha_t}\left(1 - \frac{t^2\sigma_\varepsilon^2}{\sigma_{z0}^2}\right)$$

The 2nd term inside the brackets could be estimated as the residual sum of squares from a regression of the 1991 measure on the contemporaneous measure, divided by the total sum of squares (or 1-R^2). Assuming the relationship between local educational composition in each period is the same as the relationship between deprivation indices in 1991 and 2000, I calculate that $\sigma_\varepsilon^2/\sigma_{z0}^2$ is 0.34%. The attenuation on regression coefficients resulting from our use of 1991 data as a proxy for 1995 neighbourhood composition is then about 8.5%, whilst general growth in the proportion of qualified residents leads to an upward bias of around 28%. Under these assumptions, we need to adjust $\hat{\beta}$ downwards by around 20% if we wish to interpret is as the contemporaneous of $y_{t,i}$ to z_i, whilst the elasticities should be increased by over 8%. However, we should bear in mind that a high proportion of property completions in 1995 were initiated in 1994, and may be based on the decisions made some years earlier.

10. Appendix C

The figure below shows kernel regression lines estimated by the procedure in Section 5.3, for the London area, Eastings 50000 to 56000, Northings 15000 to 21000. The bold line shows the estimate of the regression line of log-property price on the predicted proportion with high qualifications. Analytical and bootstrap standard errors as shown. The dashed bold line shows the log of the kernel regression of property prices on the proportion highly qualified. Results are mean adjusted so that log of mean property price coincides with mean of the proportion with high qualifications. Pointwise standard errors calculated by standard formulae clearly overestimate the sampling variability.

Kernel regression line for London area: specification checks



Spatial bandwidth 1 km
Bandwidth on local education 0.018 by Silvermann's rule of thumb
Linear regressors are average number of rooms and property type dummies

References

Acemoglu, D. and Angrist, J. D. (1999), 'How Large are the Social Returns to Education? Evidence from the Compulsory Schooling Laws', National Bureau of Economic Research Working Paper, Cambridge, MA.

Benabou, R. (1993), 'Workings of a City: Location, Education and Production', The Quarterly Journal of Economics August: 619-652.

Berry, B. J. L. and Bednarz, R. S. (1979), 'The Disbenefits of Neighbourhood and Environment to Urban Property', in D. Segal (ed.), *The Economics of Neighbourhood*, Academic Press: New York.

Blundell, R., Dearden, L., Goodman, A. and Reed, H. (2000), 'The Returns to Higher Education in Britain: Evidence from a British Cohort', The Economic Journal 110: F82-F99.

Burrows, R. and Rhodes, D. (1998), *Unpopular Places? Area Disadvantage and the Geography of Misery in England*, Policy Press.

Cheshire, P. and Sheppard, S. (1995), 'On the Price of Land and the Value of Amenities', Economica 62: 247-267.

Ciccone, A. and Peri, G. (2000), 'Human Capital Externalities in Cities', Unpublished manuscript.

Coleman, J. (1988), 'Social Capital in the Creation of Human Capital', American Journal of Sociology 94 (Supplement): S95-S120.

Crane, J. (1991), 'The Epidemic Theory of Ghettos and Neighbourhood Effects on Dropping Out and Teenage Childbearing', American Journal of Sociology 96(5): 1226-1259.

de Bartolome, C. A. M. (1990), 'Equilibrium and Inefficiency in a Community Model with Peer Group Effects', The Journal of Political Economy 98(11): 110-133.

Ding, C., Simons, R. and Baku, E. (2000), 'The Effect of Residential Investments on Nearby Property Values: Evidence from Cleveland, Ohio', Journal of Real Estate Research 19(1/2): 23-47.

Fernandez, R. and Rogerson, R. (1997), 'Keeping People Out: Income Distribution, Zoning and the Quality of Public Education', International Economic Review 38(1): 23-42.

Freeman, M. A. (1979), 'The Hedonic Price Approach to Measuring Demand for Neighbourhood Characteristics', in D. Segal (ed.), *The Economics of Neighborhood*, Academic Press: New York.

Galster, G. C., Tatian, P. and Smith, R. (1999), 'The Impact of Neighbours Who Use Section 8 Certificates on Property Values', *Housing Policy Debate* 10(4): 879-917.

Gephart, M. A. (1997), 'Neighbourhoods and Communities as Contexts for Development', in J. Brooks-Gunn, G. J. Duncan and J. L. Aber (eds.), *Neighbourhood Poverty: Context and Consequences for Children*, Russel Sage Foundation: New York.

Gibbons, S. (2001), 'Neighbourhood Effects on Educational Attainment', unpublished manuscript.

Gibbons, S. and Machin, S. (2001), 'Valuing Primary Schools', Discussion Paper No. 15, Centre for Economics of Education, London School of Economics.

Hansen, W. L. (1963), 'Total and Private Returns to Education', Journal of Political Economy 71(2): 128-140.

Hardle, W. (1990), *Applied Nonparametric Regression*, Cambridge University Press: Cambridge.

Harkness, S. and Machin, S. (1999), *Graduate Earnings in Britain, 1974-95*, Department of Education and Employment.

Haveman, R. H. and Wolfe, B. H. (1984), 'Schooling and Economic Well-Being: The Role of Nonmarket Effects', Journal of Human Resources XIX(3),

Jaffe, A. B. (1989), 'The Real Effects of Academic Research', The American Economic Review 79(5): 957-970.

Jencks, C. and Mayer, S. E. (1990), 'The Social Consequences of Growing Up in a Poor Neighbourhood', in L. E. Lynn, Jr. and M. G. H. McGeary (eds.), *Inner-City Poverty in the United States,* National Academy Press: Washington DC.

Kain, J. F. and Quigley, J. M. (1970), 'Measuring the Value of Housing Quality', Journal of the American Statistical Association 65(330),

Kremer, M. (1997), 'How Much Does Sorting Increase Inequality?', The Quarterly Journal of Economics: 115-139.

Lee, C.-M., Culhane, D. P. and Wachter, S. M. (1999), 'The Differential Impacts of Federally Assisted Housing Programs on Nearby Property Values: A Philadelphia Case Study', *Housing Policy Debate* 10(1): 75-93.

Lucas, R. (1988), 'On the Mechanics of Economic Development', Journal of Monetary Economics 22: 3-42.

Mincer, J. (1974), *Schooling, Experience and Earnings*, Columbia University Press: New York.

Munneke, H. J. and Slawson, V. C. (1999) 'A Housing Price Model with Endogenous Externality Location: A Study of Mobile Home Parks', Journal of Real Estate Economics 19(2): 113-131.

Nesheim, L. (2001), 'Equilibrium Sorting of Heterogenous Consumers Across Locations: Theory and Empirical Implications', unpublished manuscript.

Rilstone, P. (1996), 'Nonparametric Estimation of Models with Generated Regressors', International Economic Review 37(2): 299-313.

Rosen, S. (1974), 'Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition', The Journal of Political Economy 82(1): 34-55.

Schaffer, R. (1972), 'The Effect of BMIR Housing Policy on Property Values', Land Economics 48(3): 282-286.

Weale, M. (1992), 'Externalities from Education', in F. Hahn (ed.), *The Market: Practice and Policy*, Macmillan: Basingstoke.

CENTRE FOR THE ECONOMICS OF EDUCATION
Recent Discussion Papers

16	Richard Blundell, Lorraine Dearden Barbara Sianesi	Estimating the Returns to Education: Models, Methods and Results
15	Steve Gibbons Stephen Machin	Valuing Primary Schools
14	Costas Megir Marten Palme	The Effect of a Social Experiment in Education
13	Gavan Conlon	One in Three? The Incidence and Outcomes of LifelongLearners in the United Kingdom
12	Andrew Jenkins	Companies Use of Psychometric Testing and the Changing Demand for Skills: A Review of the Literature
11	Gavan Conlon	The Differential in Earnings Premia Between Academically and Vocationally Trained Males in the United Kingdom
		6.1.3.1
10	Peter Dolton Oscar D. Marcenaro Lucia Navarro	6.1.3.2 The Effective Use of Student Time: A Stochastic Frontier Production Function Case Study
9	Peter Dolton Mary Silles	6.1.3.3 Over-Education in the Graduate Labour Market: Some Evidence
8	Arnaud Chevalier Gauthier Lanot	6.1.3.4 The Relative Effect of Family and Financial Characteristics on Educational Achievement
7	Arnaud Chevalier	6.1.3.5 Graduate Over-Education in the UK
6	Barbara Sianesi and John Van Reenen	The Returns to Education: A Review of the Macro-Economic Literature
5	C. Harmon H. Osterbeek I. Walker	The Returns to Education: A Review of Evidence, Issues and Deficiencies in the Literature

To order a discussion paper, please contact the Publications Unit
Tel 020 7955 7673 Fax 020 7955 7595