Journal of Urban Economics 82 (2014) 12–31

Contents lists available at ScienceDirect

Journal of Urban Economics

www.elsevier.com/locate/jue

Social housing, neighborhood quality and student performance

Felix Weinhardt *

Humboldt University Berlin and Germany Institute for Economic Research (DIW), Berlin, Germany
Centre for Economic Performance (CEE, CEP) and Spatial Economics Research Centre (SERC) at the London School of Economics (LSE), London, UK
IZA, Bonn, Germany

ARTICLE INFO

Article history:
Received 16 May 2013
Revised 26 May 2014
Available online 14 June 2014

JEL classification:
J18
I21
J24
R28

Keywords:
Neighborhood externalities
Education
Urban policy

ABSTRACT

Children who grow up in deprived neighborhoods underperform at school and later in life but whether there is a causal link remains contested. This study estimates the short-term effect of very deprived neighborhoods, characterized by a high density of social housing, on the educational attainment of fourteen years old students in England. To identify the causal impact, this study exploits the timing of moving into these neighborhoods. I argue that the timing can be taken as exogenous because of long waiting lists for social housing in high-demand areas. Using this approach, I find no evidence for negative short-term effects on teenage test scores.

1. Introduction

Children who grow up in deprived neighborhoods underperform at school and later in life. In England, the most deprived neighborhoods have high concentrations of social housing (public housing) and are characterized by very high unemployment and extremely low qualification rates, high building density, overcrowding and low house prices. Growing up in social housing is associated with unfavorable outcomes: adults who lived in social housing during their childhood are more likely to be depressed, unemployed, cigarette smokers, obese, and have lower qualification levels compared to peers in their cohort who never lived in social housing (Lupton et al., 2009). The following concern arises: if living in a bad neighborhood has direct negative effects on outcomes such as school results, this could in extreme cases constitute a locking-in of the disadvantaged into a spatial poverty trap: 'once you get into a bad neighborhood, you and your children won't get out'. This might be the case because of peer group and role model effects (Akerlof, 1997; Glaeser and Scheinkman, 2001), social networks (Granovetter, 1995; Calvó-Armengol and Jackson, 2004; Bayer et al., 2008; Zenou, 2008; Small, 2009; Figlio et al., 2011), conformism (Bernheim, 1994; Fehr and Falk, 2002) or local resources such as school quality (Durlauf, 1996; Lupton, 2005).[1] In a society that believes that everyone deserves a fair chance, it is hence not surprising that this disadvantage associated to deprived neighborhoods has attracted attention from researchers and policymakers alike.[2]

This paper establishes whether moving into localized high-density social housing neighborhoods causes deterioration in the school attainment of fourteen-year-old students during the first three years of secondary education (equivalent to 6th to 8th grade in the US). The English setting offers a unique opportunity to answer this research question for two reasons.

Firstly, the geographical sorting problem needs to be overcome, which otherwise induces spurious correlations between individual and neighbors' outcomes (Manski, 1993; Moffitt, 2001). In order to identify the causal impact of neighborhood deprivation on student attainment this study exploits the timing of moving into these neighborhoods around the national age-fourteen Key Stage 3 (KS3) exam. In England, the timing of a move can be taken as

* Address: Humboldt University Berlin, Spandauer Str. 1, 10178 Berlin, Germany.
E-mail address: felix.weinhardt@hu-berlin.de

[1] It is not the aim of this paper to distinguish between these theoretical channels.

[2] Housing policies that rest on the idea of a causal channel from the place of residence to individual outcomes are inclusionary zoning and desegregation policies, as well as regeneration and mixed-housing projects, such as 'Hope VI' in the US, or the 'mixed communities' initiative in England (e.g. Cheshire et al., 2008).

http://dx.doi.org/10.1016/j.jue.2014.06.001
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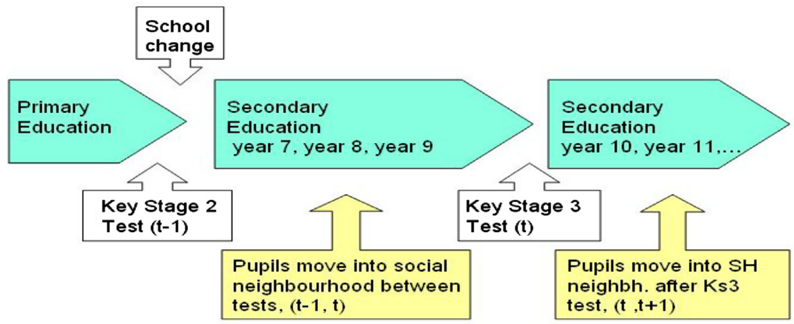

Fig. 1. The English school system and identification. Notes: The time when the KS3 exam, a national and externally marked test, is taken is denoted by t. We can now compare test score value added of students who move into deprived social housing neighborhoods before taking the KS3 test, in the period from $t-1$ to t, to students who also move into deprived social housing neighborhoods, but after sitting the KS3 exam in the period between t and $t+1$. The latter group only received a 'placebo' treatment as the future neighborhood cannot affect test scores of the test taken at time t and thus serves as control group.

exogenous because of long waiting lists for social housing in high-demand areas. In these areas, waiting times can exceed ten years, and I argue that we can therefore compare test scores of students who experience large deteriorations in neighborhood quality before the exam, to test scores of other students who will be subjected to the same neighborhood treatment in the future (Fig. 1). Naturally, a student's result in the KS3 exam can only be influenced by the low quality of her new neighborhood if she moves into this neighborhood before taking the test. Later movers only receive a (future) 'placebo' treatment and serve as natural control group as they are likely to share many unobserved characteristics common to social tenants.[3] We know that students from deprived family backgrounds are prioritized, but identification only relies on them being prioritized in a similar way before and after the KS3 test. This means that we can relax the usual assumption that social housing neighborhood allocation is quasi-random as such (e.g. Oreopoulos, 2003). Time-invariant preferences or unobserved institutional arrangements that could give rise to neighborhood sorting can be captured by the neighborhood fixed effect. The remaining assumption required for identification is that allocation and individual sorting preferences for particular neighborhoods do not change over the study period. In support of this assumption, I show that a rich set of individual characteristics including earlier age-7 and age-11 test scores fail to predict the time of the move. I interpret this as direct evidence in favor of the validity of the identification assumption of quasi-random timing.

Secondly, nation-wide census data makes it possible to track individual residential mobility for four cohorts of students in England; the study is therefore not limited to a small number of neighborhoods or of cities. I use the Census 2001 Output Areas (OA) to define a neighborhood, which are small geographical units of 125 households on average.[4] The average OA contains about 4.5 same-age students, who on average attend 2.5 different schools. The fact that there exists no direct linkage between residential location and secondary school choice in England allows the simultaneous inclusion of school and neighborhood fixed effects. The richness of the data also allows including controls for a potential direct effect of moving, earlier attainment and family background.

The main finding of this study is that early movers into deprived social housing neighborhoods experience no negative short-term effects on their school attainment relative to late movers. While it is demonstrated that there are large negative associations between moving into deprived areas and school outcomes, these negative correlations cease to exist once controlling for group-specific observable and unobservable characteristics in a difference-in-difference framework. In the most demanding specification, the estimate for the neighborhood effect on teenage test scores is *positive* and insignificant. At the five per cent significance level, these estimates allow us to reject negative effects larger than 1.2 per cent of a standard deviation in teenage test scores, coming from large deteriorations in neighborhood quality such as a one standard deviation increase in local unemployment rates and share of lone parents with dependent children. I therefore conclude that these results are sufficiently precise to provide strong evidence against negative short-term effects from moving into deprived high-density social housing neighborhoods during the formative teenage years.

To the best of the author's knowledge, exploiting the timing of moving when waiting lists are long is a novel strategy to study neighborhood effects.[5] Besides this methodological innovation, the finding of no negative effects on school outcomes from moving into high-density social housing projects informs the literature, where similar conclusions have been reached with lower precision in the estimates.

The rest of the paper is structured as follows: The next section briefly described related literature. Section 3 outlines in detail the empirical strategy of this paper. Section 4 describes the institutional setting and Section 5 the data. Section 6 discusses the results and Section 7 presents a battery of robustness checks before I summarize and conclude.

2. A very short review of the related literature

For educational outcomes the only existing and credible experimental study, the Moving to Opportunity (MTO) intervention, a mobility voucher scheme, finds little evidence for neighborhood effects in both the short and the long-run (Katz et al., 2001; Sanbonmatsu et al., 2006; Kling et al., 2007; Ludwig et al., 2012, 2013).[6] In contrast, the non-experimental literature tends to find evidence in favor of neighborhood effects on educational outcomes.

[3] This strategy is related to Rothstein (2010) who studies effects of teacher quality and exploits the fact that future teachers cannot affect contemporaneous value added test scores.

[4] For comparison: OAs are smaller compared to US Census Tracts or Block Groups and more comparable to Census Blocks, though these are even smaller than OAs on average and have larger variation in size.

[5] Existing research used instrumental variables (Cutler and Glaeser, 1997; Goux and Maurin, 2007); aggregation (Card and Rothstein, 2007); institutional settings (Gibbons, 2002; Oreopoulos, 2003; Jacob, 2004; Gould et al., 2004; Gurmu et al., 2008; Goux and Maurin, 2007); fixed effects (Aaronson, 1998; Bayer et al., 2008; Gibbons et al., 2013) or experimental setups (Katz et al., 2001; Kling et al., 2007; Sanbonmatsu et al., 2006; Ludwig et al., 2012, 2013).

[6] The MTO has been questioned by some because of its focus on relatively small neighborhood-level changes (i.e. small 'treatments') and limited geographical representativeness (Quigley and Raphael, 2008; Clampet-Lundquist and Massey, 2008; Small and Feldman, 2012).

Goux and Maurin (2007) study the effect of close neighbors in France and find strong effects on end of junior high-school performance and Card and Rothstein (2007) find effects of city-level racial segregation on the black-white test score gap.[7]

In contrast, Jacob (2004) does not find effects of public housing on student achievement using demolitions as an instrument. However, Jacob cannot reject negative short-term effects on test scores of up to 0.10 standard deviations.[8] Similarly, comparing the experimental and control groups of the MTO, Ludwig et al. (2013) cannot reject long-term ITT-effects on reading and mathematics assessments smaller than 0.10–0.15 standard deviations for female and male youth.[9] More comparable to the short-term nature of this study, Kling et al. (2007) cannot reject effects of about 0.13 standard deviations in a composite education measure five years after random assignment, although there find significant differences by gender. Finally, Sanbonmatsu et al. (2006) cannot reject effects of 0.12 standard deviations on combined reading and mathematics scores comparing MTO treatment and control groups of 11-to-14 year-old children, which is the same age group studied here.

The conclusions of this paper are based on very precise estimates. We can reject very small short-term effects greater than 0.012 standard deviations, from moving into highly deprived social housing neighborhoods up to three years prior to the national tests.

3. Empirical strategy

This study focuses on identifying the effect on educational attainment of moving into high-density social housing neighborhoods. The worry is that these students carry unobserved characteristics that explain their educational underperformance which are also linked with the fact that their parents got admitted into social housing in the first place. This sorting would generate spurious correlations between neighborhood characteristics and individual outcomes even in the absence of any neighborhood effects.[10] As a novel strategy, this study exploits the timing of the move around national Key Stage 3 (KS3) tests to control for all observed and unobserved factors that are common to students moving into high-density social housing neighborhoods. Fig. 1 illustrates this identification strategy. This section derives the final difference-in-difference (DID) model starting by assuming that test scores can be modeled as a linear function of neighborhood, school and individual characteristics in the following way:

$$y_{ignsct} = \mathbf{Z}'_{nt}\beta + \mathbf{x}'_{it}\gamma + \mathbf{x}'_{it}\delta t + \mathbf{S}'\boldsymbol{\varphi} + \mathbf{S}'t\kappa + c_c + c_c t + \varepsilon_{ignsct} \tag{1}$$

where y_{ignsct} denotes test scores of individual i of group g, in neighborhood n, school s, cohort c in year t. $\mathbf{Z}_{nt}$ denotes time-varying neighborhood characteristics that could influence attainment at school, like the absence of role models, etc. The vector $\mathbf{x}$ denotes individual-level characteristics that affect test scores, like family background characteristics or earlier test scores. I further allow these characteristics to have a time-varying effect on test outcomes, denoted by $\mathbf{x}'_{it}\boldsymbol{\delta}t$. The matrix $\mathbf{S}$ denotes school-level characteristics and c allows for different intercepts for the different cohorts, and both could have effects depending on the timing, as well. Further, let us assume that the error term contains the following elements:

$$\varepsilon_{ignsct} = \alpha_i + z_n + z_n t + s_s + s_s t + \phi_g + \phi_g t + e_{ignsct} \tag{2}$$

where α_i represents unobserved individual effects such as motivation, z_n unobserved neighborhood characteristics, s_s unobserved year school quality and ϕ_g unobserved characteristics of belonging to group g. Let us think of gas representing time-invariant characteristics, which are common to students who move into social housing neighborhoods. I further allow the unobserved neighborhood, school and group characteristics to have time-varying effects through $z_n t$, $s_s t$ and $\phi_g t$. Lastly, e_{ignsct} is the error term, which we assume to be random. The problem is that all former components might correlate with individual and neighborhood specific variables from Eq. (1) for the discussed reasons and hence bias any estimates. The first step to potentially overcome these problems is to difference the equation:

$$(y_{ignsct} - y_{ignsct-1}) = (\mathbf{Z}_{nt} - \mathbf{Z}_{nt-1})'\beta + \mathbf{x}'_i\delta + \mathbf{S}'\kappa + \mathbf{c_c} + (\varepsilon_{ignsct} - \varepsilon_{ignsct-1}) \tag{3}$$

where $(y_{ignsct} - y_{ignsct-1})$ is the test-score value added between KS2 and KS3 modeled as a function of changes in the neighborhood environment $(\mathbf{Z}_{nt} - \mathbf{Z}_{nt-1})$, individual characteristics $\mathbf{x}_i$ and school-characteristics $\mathbf{S}$ that affect value-added. The time-independent effects all cancel out. The differenced error term now has the following components:

$$(\varepsilon_{ignsct} - \varepsilon_{ignsct-1}) = z_n + \phi_g + s_s + \upsilon_{ignsct} \tag{4}$$

We are left with unobserved neighborhood characteristics that could affect value added z_n, the group effects that have a time-varying effect ϕ_g, unobserved school-level variables that affect value-added s_s and υ_{ignsct}. Note that I will cluster the error term at the neighborhood-level to allow for local correlations in the error term matrix. This differenced error term does not contain any unobserved characteristics that affect test score levels. In some of my regressions I can include fixed effects to control for two of the remaining three non-random unobserved components z_n, and s_s.

From an identification point of view this model is preferable to the levels-model presented earlier. This is because all unobserved constant factors, in particular family background or individual motivation, are now controlled for and cannot generate spurious correlations through the sorting mechanism. Furthermore, by including fixed effects for neighborhoods and schools unobserved constant local factors affecting value-added can be taken care of. However, a remaining worry is that students who move into social housing share individual or background characteristics that are unobserved and correlate with neighborhood changes. These unobserved group characteristics are captured by ϕ_g in Eq. (4) and cannot be controlled for directly. My strategy addresses this final concern by comparing early movers to late movers,[11] so students who experienced a neighborhood level treatment before sitting the KS3 exam at time t to students who moved later and hence only received a 'placebo' treatment as future neighborhood changes cannot affect past value added.

In order to mirror the setup from Fig. 1 in a regression framework, we need to define interaction variables for moving into a high-density social housing neighborhood:

[7] In addition, there is a related literature that shows that peers matter in school (i.e. Sacerdote, 2001; Carrell et al., 2009; Lavy et al., 2012), and that neighborhoods matter for labor market outcomes (Cutler and Glaeser, 1997; Ross, 1998; Ananat, 2007; Weinberg, 2000, 2004; Bayer et al., 2008), although again the MTO and Oreopoulos (2003) do not find evidence for neighborhood effects on labor market outcomes. For a full review of the related literature see Ross (2011).

[8] This is based on 2SLS estimates reported in Table 6 in Jacob (2004).

[9] See Panel C in Online Appendix Table 10.

[10] A further problem in neighborhoods effects research is the "reflection problem". This issue arises because individuals might not only be affected by other individuals in their neighborhood but might equally affect these themselves (Manski, 1993). If neighborhood effects exist, this causes a reverse causality problem that biases the neighborhood coefficients upwards. Since this study finds no effects once we control for unobserved effects of moving into social housing, we do not need to be concerned with the reflection problem.

[11] I follow the literature (i.e. Katz et al., 2001; Jacob, 2004) and rely on students who move to generate variation in the neighborhood variables $(z_{nt} - z_{nt-1})$, since neighborhoods change very slowly over time.

$$D(SH)_{i,t-1,t}\begin{cases}=1 \text{ if pupil moves into social housing between } t \text{ and } t-1\\ =0 \text{ otherwise}\end{cases}$$
$$D(SH)_{i,t1,t+1}\begin{cases}=1 \text{ if pupil moves into social housing between } t \text{ and } t+1\\ =0 \text{ otherwise}\end{cases}$$
$$D(SH)_{i,t-1,t+1}\begin{cases}=1 \text{ if pupil moves into social housing between } t-1 \text{ and } t+1\\ =0 \text{ otherwise}\end{cases}$$

I use these interaction variables to proxy for neighborhood quality changes ($\mathbf{Z}_{nt}-\mathbf{Z}_{nt-1}$), as a catchall proxy for the large deteriorations in neighborhood quality these students experience.[13]

One concern is that a move might also directly affect value added, and not only indirectly through the change in neighborhood quality. The 'placebo' group only moves after taking the test so that the neighborhood quality change cannot affect test scores, but equally they do not move before taking the test. If there was a direct effect of mobility on test scores, i.e. through disruption, this could bias the estimates. To allay these concerns I can difference out the pure effect of moving using the population of students who move but not into social housing. To do this, I analogously define interaction variables $D(M)_{i,t-1,t}$, $D(M)_{i,t,t+1}$ and $D(M)_{i,t-1,t+1}$ for students who move in the relevant periods but do not move into social housing neighborhoods.

With these ingredients we can now construct a difference-in-difference estimate from Eqs. (3) and (4) using the interaction variables defined above. To see this, let us first write down this model using the interaction terms for students who moved into high-density social housing neighborhoods between $t-1$ and t:

$$y_{ignsct}=\gamma_1 D(SH)_{i,t-1,t}+\gamma_3 D(M)_{i,t-1,t}+\theta y_{ignsct-1}+\mathbf{x}_\mathbf{i}'\delta+\mathbf{S}'\kappa + c_c+z_n+\phi_g+s_s+v_{ignsct} \quad (5)$$

where y_1 gives the effect of moving into a high-density social housing neighborhood, which substitutes for $\mathbf{Z}_{nt}-\mathbf{Z}_{nt-1}$ in Eq. (3),[12] and $D(M)$ controls for direct effects of moving. I also relax the assumption that θ equals one and instead of differencing test scores manually on the left-hand side include past test-scores as control variable on the right-hand side of the equation.[14]

Note that we can write down a similar model for students who moved into high-density social housing neighborhoods after sitting the KS3 test between time t and $t+1$:

$$y_{ignsct}=\gamma_1 D(SH)_{i,t,t+1}+\gamma_3 D(M)_{i,t,t+1}+\theta y_{ignsct-1}+\mathbf{x}_i'\delta+\mathbf{S}'\kappa + c_c+z_n+\phi_g+s_s+v_{ignsct} \quad (6)$$

The only difference is that this equation estimates the placebo effect of moving into high-density social housing neighborhoods between t and $t+1$ on test scores taken at time t. We can now combine Eqs. (5) and (6) into a single equation using the indicator variables and the fact that $D(SH)_{i,t-1,t+1}\supseteq D(SH)_{i,t-1,t}$ and $D(SH)_{i,t-1,t+1}\supseteq D(SH)_{i,t,t+1}$:

$$y_{ignsct}=\gamma_1 D(SH)_{i,t-1,t}+\gamma_2 D(SH)_{i,t-1,t+1}+\gamma_3 D(M)_{i,t-1,t} + \gamma_4 D(M)_{i,t-1,t+1}+\theta y_{ignsct-1}+\mathbf{x}_i'\delta+\mathbf{S}'\kappa+c_c+z_n+s_s + v_{ignsct} \quad (7)$$

This equation estimates γ_1, which is the effect of moving into a high-density social housing neighborhood on KS3 test scores at age-14, controlling against characteristics of the placebo group of students who moved after the test captured by γ_2. Potential direct effects of moving are absorbed by the general moving dummies γ_3 and γ_4. Since there might be further differences between students moving before t and after t, I include previous test scores $y_{ignsct-1}$, individual characteristics $\mathbf{x}_i$, school characteristics $\mathbf{S}$ and a cohort dummy c_c. As I discuss in Section 7 these observable differences turn out to be unimportant. A remaining worry is that –unobserved to the researcher–, early movers might move to systematically different neighborhoods. To control for this I can include neighborhood-fixed effects z_n in some of my specifications, as well as school fixed effects s_s to control for any unobserved school quality differences between early (the treatment group) and late (placebo/control group) movers.

'Importantly, the unobserved constant characteristics for students moving into social housing neighborhoods ϕ_g drop out, as this term is now perfectly collinear with $D(SH)_{i,t-1,t+1}$. This means that test score improvements of students who move into high-density social housing neighborhoods are now directly compared to improvements of other students who move into high-density social housing neighborhoods. Any constant unobserved group characteristics that are correlated with test scores and family background, for example, are therefore taken care of. This is the main advantage of the DID setup where the remaining assumption for identification is that the timing of moving is quasi-random. Before turning to the data directly, the following section describes the institutional setting in detail, which I believe already gives a first indication that the common trends assumption might be met in this context.

4. Institutional setting

4.1. The social housing sector in England

4.1.1. A short account of demand and supply since the Second World War

The quality and social composition of social tenants has changed greatly over the past sixty years. After the Second World War, when Britain, like most other European countries, faced an acute housing shortage, social housing provided above-average quality accommodation. A move into social housing was regarded as moving up from private renting and most houses had gardens and good amenities (Lupton et al., 2009). The social housing sector continued to expand during the 1960s and 1970s and peaked at thirty-one per cent of the total English housing stock in 1979 (Hills, 2007, p. 43). Social housing still provided much diversity in terms of both, quality and social and neighborhood composition, but some of the older stock required refurbishments. As a response to this, housing associations, non-profit entities that provide social housing, started to grow in number and importance (Lupton et al., 2009). From the 1980s until today the social sector shrank both in absolute size and importance relative to other types of tenure. Construction activity in the social sector declined sharply from almost 150,000 dwellings to 50,000 dwellings/year in the early 1980s and stagnated on the historically lowest level since the Second World War at around 20,000/year since the late 1990s (Hills, 2007). Councils and housing associations provided about four million social dwellings in 2004 (about eighteen per cent of stock), down from almost six million dwellings in 1979. This decline of social housing resulted from a combination of the "right-to-buy" scheme introduced by Margaret Thatcher in 1980 and the aforementioned public spending cuts on new construction (Hills, 2007, p. 125). The "right-to-buy" scheme altered the socioeconomic composition of social tenancy as it allowed those who could afford it move into owner-occupation (Hills, 2007; Lupton et al., 2009). Admission criteria also

[12] This catchall neighborhood treatment is discussed in detail in Section 5.5.

[13] There is a worry that the coefficient on the past test score will be downward biased if the KS2 test only measures ability with an error (see Todd and Wolpin, 2003). In this application however the way we control for past test scores – or if we control for past test scores at all, makes little difference to the estimates. This is because the placebo group is extremely similar to the treatment group in terms of observable characteristics, which I come back to in Section 7.

changed during this period when the Homeless Persons Act of 1977 forced councils to provide accommodation to certain groups in extreme need (Holmans, 2005). These trends continued through the 1980s and 1990s. As a result of these changes and the increasingly needs-based allocation, in 2004 seventy per cent of social tenants belonged to the poorest two-fifths of the income distribution and hardly anyone to the richest fifth. This is in contrast to 1979 when twenty per cent of the richest decile lived in social housing (Hills, 2007, pp. 45, 86).

Today, demand for social housing greatly exceeds supply. About nine million social renters live in four million social dwellings (Turley, 2009). With very small but if anything negative *net* changes in social housing supply spaces can only free up if existing tenants die or move out. Movement within or out of the sector is very low and eighty per cent of social tenants in 2007 were already there in 1998, if born (Hills, 2007, p. 54). Regan et al. (2001, executive summary) concludes in a qualitative study on housing choice and affordability in Reading and Darlington that "Moving within social housing was curtailed by allocation procedures and a lack of opportunity to move or swap properties". Quantitative evidence confirms that mobility within the social rented sector is extremely low, in spite of the mobility schemes that the government started to implement recently (Hills, 2007, p. 109). It is still the exception to move within the social housing sector once one gets in. As a result, there are currently 4.5 million people (or about 1.8 million households) on waiting lists for social housing. Taking these numbers at face value, if nothing were to change and no one was born into social housing, this would mean that about 800,000 dwellings (20 per cent of four million) could free up every ten years. Even assuming zero new demand over the coming years, it would take over twenty-two years to provide housing to all currently on a waiting list.

Taken together, after the changes in housing supply and the introduction of needs-based eligibility criteria the sector has been remarkably stable since the late 1990s. This is assuring given that the DID framework rests on common trend assumptions which is further discussed in the following section.[14]

4.1.2. Social housing allocation and waiting times

The social housing allocation system as it exists today continues to operate on a needs-based system where the Homelessness Act 2002 defines beneficiaries. Families with children are treated as a priority. In the current situation of excess demand it is in fact very difficult to get into social housing without belonging to one of the needy groups. While the needy groups are defined nationally, provision is decentralized and administered through councils or housing associations. Local authorities operate different systems, some using a banding system and others a points-based system to ensure that those with the highest need and waiting time get a permanent place in social housing next (Hills, 2007).[15] Take-up rates are extremely high, though no representative data exists to show this. Regan et al. (2001) writes that one of their interviewees in Reading who rents from a social landlord complained: "Most of the people I know who have been offered flats or houses or anything have no choice... it is that or nothing" (2001, p.22).

Note that in the DID framework it is not generally required for identification that people cannot exert influence on the neighborhood or place where they are offered social housing.[16] This is because any sorting generated through the allocation procedures or institutional factors, such as discrimination against certain types of applicants, do not cause bias as long as they are time-consistent. Intuitively, if a social planner always offers places in nicer neighborhoods to families with certain characteristics for example, this is going to happen equally before and after the KS3 test. The fact that the centrally defined eligibility criteria stayed unchanged over the study period is therefore ensuring. Furthermore, in some specifications I can include neighborhood destination fixed effects. In these specifications we are effectively comparing the value added in test scores of students who moved into the same neighborhood, but one group moving before taking the test at time t, while the other group moved just afterward. Any remaining constant unobservable characteristic that is related to individual neighborhood quality will be captured by the fixed effect.

Since allocation of social housing is needs based, we are still worried that unobserved negative shocks that made the family eligible for the social housing sector might also affect test scores negatively. To address this concern, the DiD strategy exploits the fact that people who apply for social housing in England are not directly allocated a place but usually have to remain on waiting lists for years. The idea is that if people have been on the waiting list for social housing for many years, current changes in characteristics cannot be correlated to the timing of the neighborhood they eventually move into. Unfortunately no individual-level data on actual waiting times is available, which would allow us to ensure that waiting times are long directly. Anecdotal evidence suggests that waiting times easily extend to periods of seven to fourteen years.[17] Fortunately, waiting list related information is available by Local Authority (LA), of which about three hundred exist in England. To ensure waiting times are sufficiently long, I only include in the analysis local authorities in which at least five per cent of the population have been on a waiting list in the year 2007 (Fig. 2). The share of the population on a waiting list is certainly not a perfect proxy for waiting times but should be highly correlated. The hope is that this ensures that families who get into social housing at different points in time are very similar in their average characteristics. To address this concern, I can control for factors such as ethnicity, free school meal status, gender and previous test scores. We will see that including these controls does not affect the conclusions.

Because I cannot show directly that the waiting times are sufficiently long the skeptical reader might still believe that a negative shock, that made a family eligible for social housing in some areas, may affect the test scores of early and later movers differently. Note that in the standard additive test score production function these shocks would already be captured by the end of primary school KS2 test scores $y_{ignsct-1}$, at least for the early movers. However, Section 7 returns to these issues and shows that early and late movers look statistically identical in their observable characteristics including prior age-7 (Key Stage 1) and age-11 (Key Stage 2) test scores, which I interpret as evidence in favor of the quasi-random timing assumption.[18]

[14] If immigrants received priority in social housing allocation, changes in migration flows could confound my analysis. This is not the case because immigrants are generally ineligible for social housing, as pointed out by Rutter and Latorre (2009).

[15] About a third of local authorities complement their waiting list system with a choice-based element, where new social housing places are announced publicly and prospective tenants are asked to show their interest in each specific place (Hills, 2007, p. 163). The prospective tenant with the highest score as determined through the waiting list mechanisms then gets the offer. However, most places are still directly allocated through the council or housing association.

[16] As in Oreopoulos (2003) or Goux and Maurin (2007).

[17] The London Borough of Newham publishes general waiting times by housing stock: http://www.webcache.googleusercontent.com/search?q=cache:bxpvuuEw4-WIJ:www.newham.gov.uk/Housing/HousingOptionsAndAdvice/ApplyingForCouncil-HousingOrHousingAssociationProperty/AverageWaitingTimesforAllocatedHousing.htm+ social+hosuing+waiting+times+uk&cd=5&hl=en&ct= clnk&gl=uk.

[18] A further issue is that parents might save on rent when they move into social housing. As it turns out this is unlikely to be the case in the English setting since parents eligible for social housing are likely to be eligible for housing benefits which are adjusted accordingly. This is explained in the Appendix. I also test for direct income effects directly in Section 7.1.2 (and do not find any).

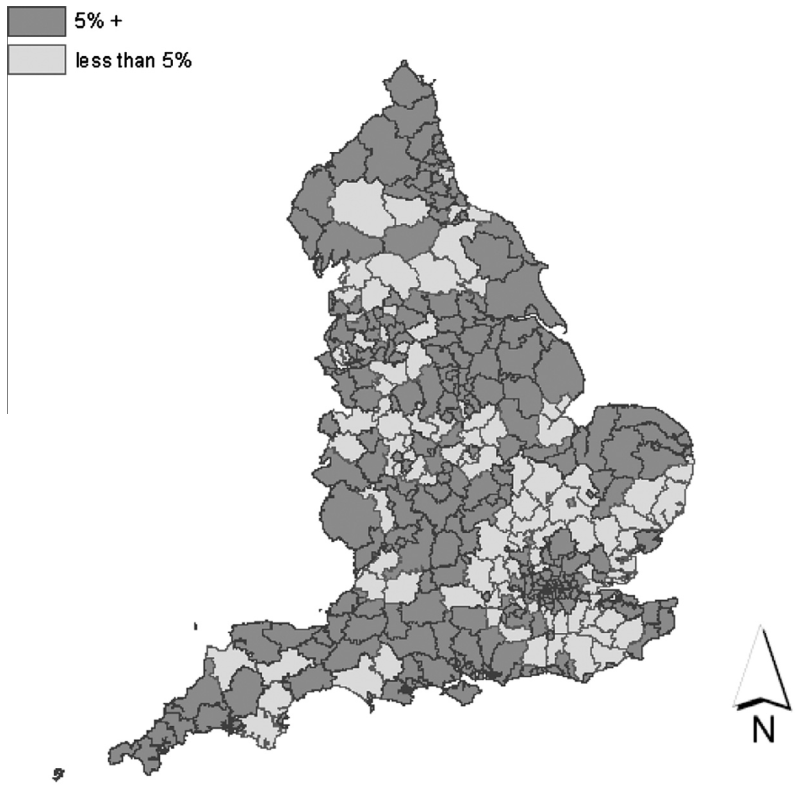

Fig. 2. Share of population on waiting list 2007, Local Authority level.

In addition, note that more general changes in the housing sector might affect demand for social housing. In the context of this study it is important to note firstly that England experienced no general housing bubble from the early 1990s until recently. The House Price Index published by the UK Land Registry shows that the market only started turning in 2007–2008, which is later than in the US (see Case et al., 2012), to a much lesser extend and too late for affecting waiting lists for people moving into social housing neighborhoods during our study period.[19] This is important because, for example, families waiting seven years would have to have joined to waiting lists between 1995 and 2002 in order to move in between 2002 and 2009. However, during these years there was no major crisis in the English housing market and affordability indexes remained roughly stable.[20] Secondly, Local Authority waiting lists for social housing are highly correlated over time and there is very little variation in the rank order of LAs by waiting list length. More specifically, 1998 and 2004 waiting list are similarly highly correlated as 1998–2010 waiting lists ($r = 0.888$ and 0.893 respectively, 1998 being the earliest year for that data is available).[21] This is assuring because it again indicates the absence of region-specific demand shocks that could make social housing more or less attractive relative to other tenancy types. I return to these issues regarding the common trends assumption in Section 7, where I show that early and late movers are balanced with regard to a rich set of pre-determined individual and neighborhood characteristics.

[19] HP data: http://www.landregistry.gov.uk/__data/assets/file/0004/83614/Indices_SA_SM.csv [05/20/14].

[20] Affordability index: http://www.economicshelp.org/wp-content/uploads/2012/07/nw-affordability-index.png [05/20/14].

[21] Data source: Department for Communities and Local Government, Live Table 600, URL https://www.gov.uk/government/-uploads/system/uploads/attachment_data/file/267535/LT600.xls [05/20/14].

4.2. The English school system

The English school system is organized into four "Key Stages", in which learning progress is assessed at the national level. Of interest for this study are the Key-Stage 2 (KS2) assessment at the end of primary/junior School and the Key-Stage 3 (KS3) assessment, which assesses students' progress in the first three years of compulsory secondary education (see Fig. 1). Note that there is no skipping or repeating in England and that year-groups/grades and cohorts are thus identical. The KS2 assessment is at the age of 10/11, while the KS3 is carried out at the age of 13/14. In the main analysis I use the average performance across the three core subjects English, mathematics and science to measure attainment. Since I compute cohort-specific percentiles of the respective KS2 and KS3 scores, individual results between the two tests and cohorts are directly comparable. The KS3 score is of no direct importance to parents or housing organizations and is not a high-stakes test in a sense that anyone would specifically avoid moving before the test or time a move around it. On the other hand, it correlates highly with later school and labor market outcomes and is therefore of general policy interest.

It is important to notice that access to secondary schools is generally non-selective. As a result, and in contrast to many other countries, there is no exact mapping between neighborhoods and schools. Indeed, five students who live in the same postcode on average attend two to three different secondary schools, and every secondary school has students from about sixty neighborhoods. This feature of the English school system will allow to control for school fixed effects without losing the neighborhood-level variation (similar as in Gibbons et al., 2013).

5. Data and descriptive statistics

5.1. Combining various datasets

To undertake this analysis I have combined a number of datasets, which are briefly summarized in Appendix Table A1. These are the student-level annual school census, the national Key Stage exam results, the UK Census of Population 2001, Local Authority-level information on waiting lists and house prices.

Using these data I can construct a student-level panel of four cohorts for five consecutive years and track individual students from their first (academic year seven) to fifth year (academic year eleven) in secondary education with merged-in Key Stage national test scores.[22] For the first cohort this corresponds to the period from 2001/02 to 2005/06, and for the second from 2002/03 to 2006/07, and so on. I can also use the residential information of the school census to identify all students who have moved during the academic years eight to eleven on an annual basis. Next, I use the Census 2001 Output Area (OA) definition to delimit a 'neighborhood'. OAs were originally constructed to include a comparable number of households: each contains about four to five postcodes and on average 125 households. In this respect, this study follows Gibbons et al. (2013) who examine various spatial scales to study neighborhood effects in England and choose the Output Area for the main analysis. The average Output Area contains 4.5 students who attend 2.5 different schools. This census was collected one year before my analysis starts and I extract pre-treatment neighborhood-level information on the male unemployment rate, the level of education, the level of car ownership, building density, overcrowding, average number of rooms per household and the percentage of lone parents with dependent children. Notice that even if annual information was available I would prefer to use the pre-dated 2001 Census information because later changes in neighborhood quality could be endogenous to variation that I am using for the estimation.

The descriptive statistics for this combined full dataset are shown in Table 1. Panel A summarizes characteristics of over 1.7 million students, Panel B shows descriptive statistics for over 157,000 year-7 neighborhoods weighted by student population and Panel C shows student to teacher ratios of 3098 schools, again weighted by student numbers.

5.2. Sample selection

I restrict the sample to comprehensive, grammar, secondary modern and technical schools that span the whole period between KS2 and two years after the KS3. Other less common school types in England, such as middle schools, are not organized around the Key Stages the same way as shown in Fig. 1 and often require school changes after year nine, which could confound any analysis that focuses on moves between years seven and eleven. The schools included enroll ninety per cent of students in English state education and this reduces the full sample to about 1.57 million students as summarized in column 2 of Table 1.

Next, as discussed in Section 4.1.2, I limit the analysis to Local Authorities where at least five per cent of the population is on a waiting list. Long waiting times are crucial to ensure quasi-random timing of moving into social housing. This qualification results in a reduction of the sample to about 1.12 million students (column 3 of Table 1). Similarly, the number of (year-7) neighborhoods included reduces from almost 150,000 to about 110,000. While differences are small, overall the remaining students and neighborhoods have slightly less favorable characteristics and conditions when compared to the previous or the full sample (Table 1). For instance, average KS3 test scores are down to 49.453 (from 50.522) and unemployment rates up to 4.7 per cent (from 4.4 per cent). Overall, I still believe these differences are small enough to justify this sample restriction. In the absence of individual-level data on waiting lists I find it preferable to increase internal validity as much as possible by focusing on Local Authorities with long waiting lists in order to ensure long waiting times and identification.

Finally, there is a small fraction of students who move more than once during the study period. These students cannot be used to control for the effect of a single relocation because they relocated multiple times. I exclude these students so that I do not have to deal with defining separate moves conceptually but this omission has no impact on results and reduces the sample by less than 0.5 per cent. In this final sample we have 1,063,435 students living in 109,071 neighborhoods in year 7. Note that since some neighborhoods only appear in some cohorts, the average Output Area contains 4.2 same-age (i.e. same-cohort) students.

Descriptive statistics for the final sample used in the analysis are shown in the last column of Table 1. The sample contains over one million students with average scores in the national KS2 and KS3 percentiles of about 50 points. About fourteen percent are eligible for free school meals; half are male and 81.8 per cent of while British origin. Panel B shows student-weighted characteristics of the 109,084 neighborhoods they live in at the beginning of the observation period in year 7: the average unemployment rate was at 4.6 per cent in 2001, 7.5 per cent are a lone parent with dependent child and 82.5 per cent have access to a car or van.

5.3. Descriptive statistics for subgroups

In addition to the last column of Table 1, Table 2 contains summary statistics for various subgroups of the main dataset: students who either live in a social housing neighborhood throughout their academic years seven to eleven (column 1), students who move into social housing neighborhoods during this period (columns 2, students who stay in a non-social housing neighborhood (column 3), and other movers (column 4).

We can see from panel A, for example, that these students have Key Stage test scores much below the national average. Their KS2 scores average at only 38.15 points and the respective KS3 scores are even lower at 35.21 percentile points. These students are the weakest when starting secondary school, but results deteriorate even further up to KS3. Moreover, almost half of them are eligible for free school meals (FSME), which is a proxy for a low-income background. Panel B shows the respective student-weighted neighborhood characteristics before moving (year 7). Columns (3) and (4) give summary statistics for students who lived in non-social housing neighborhoods throughout, or move between non-social housing neighborhoods respectively. We can see that while the movers (4) have slightly lower scores, all these students generally do much better at school and live in much nicer neighborhoods, too, compared to columns (1) and (2). Finally, Panel C shows only small differences in student–teacher ratios of schools attended by these subgroups.

One important take-away from this Table is that students who stayed in social housing (column 1) do not look entirely different to students who moved into social housing neighborhoods during the study period (column 2). Both groups obtain KS results far below the average. As discussed, one general problem in neighborhood research is that neighborhoods do not change much over time.

[22] The school census is collected in the middle of each January, close to when the national Key Stage 3 tests are taken in May. I ignore this time mismatch of four months here, but address it directly in one of the robustness checks.

Table 1
Construction of final dataset, descriptive statistics.

	(1) Full dataset		(2) Incl. school selection		(3) Incl. waiting list criteria		(4) Not moving more than once	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Panel A: Individual characteristics								
Key Stage 2 Score	50.320	28.855	50.522	28.883	49.882	28.850	50.258	28.843
Key Stage 3 Score	50.330	28.858	50.256	28.936	49.453	28.845	49.910	28.839
Changed school before, yr 7–9	0.106	0.308	0.041	0.197	0.037	0.190	0.031	0.172
FSME eligibility year 7	0.134	0.341	0.138	0.345	0.147	0.354	0.142	0.349
FSME eligibility year 8	0.130	0.336	0.133	0.340	0.142	0.349	0.137	0.344
FSME eligibility year 9	0.123	0.329	0.127	0.333	0.135	0.342	0.130	0.336
Gender (male = 1)	0.499	0.500	0.498	0.500	0.498	0.500	0.499	0.500
Ethnicity-White British Is.	0.837	0.370	0.833	0.373	0.818	0.386	0.818	0.386
Ethnicity-Other White	0.016	0.127	0.017	0.128	0.019	0.135	0.018	0.135
Ethnicity-Asian	0.061	0.240	0.063	0.243	0.068	0.251	0.069	0.253
Ethnicity-Black	0.029	0.167	0.030	0.170	0.037	0.188	0.036	0.186
Ethnicity-Chinese	0.003	0.055	0.003	0.056	0.003	0.057	0.003	0.058
Ethnicity-Mixed	0.024	0.152	0.024	0.152	0.025	0.156	0.025	0.155
Ethnicity-Other	0.006	0.079	0.007	0.081	0.008	0.089	0.008	0.088
Panel B: Neighborhood characteristics, pre move (if any)								
Unemployment rate	0.044	0.038	0.045	0.039	0.047	0.038	0.046	0.038
Level 4 + qualification[1]	0.624	0.132	0.623	0.133	0.619	0.131	0.620	0.131
Access to car or van[2]	0.839	0.152	0.835	0.154	0.823	0.157	0.825	0.157
Lone parent with dep. child	0.072	0.060	0.073	0.060	0.075	0.061	0.075	0.061
Limiting long term illness	0.336	0.102	0.339	0.103	0.343	0.101	0.343	0.101
Overcrowding[3]	0.063	0.074	0.064	0.075	0.070	0.082	0.070	0.082
Number of rooms	5.482	0.854	5.471	0.855	5.399	0.840	5.407	0.842
Population density[4]	50.908	50.511	51.804	51.691	55.394	56.849	55.216	56.729
Average house price[5]	0.952	0.543	0.949	0.552	0.926	0.533	0.931	0.534
Panel C: Secondary school characteristics, year 7								
Student to teacher ratio	15.911	1.965	15.769	1.741	15.801	1.732	15.798	1.730
Number of students	*1,737,140*		*1,570,403*		*1,117,566*		*1,063,435*	
Number of neighborhoods (year 7)	*158,731*		*149,586*		*109,610*		*109,071*	
Number of schools	*3089*		*2561*		*2444*		*2442*	

Notes: Column (1) is the full National Pupil Database (NPD) with non-missing information for four cohorts taking their KS2(3) tests in 2001(04) to 2004(07). Column (2) keeps only non-selective state schools, column (3) only students always living in a Local Authority with at least 5% of the population on the social housing waiting list, column (4) exclude students moving more than once. Rows: Panel A: Key Stage 2 (Key Stage 3) is the national assessment at age 11 (14) percentalised at cohort-subject level. FSME is free school meal eligibility. Panel B shows data from the 2001 UK Census Output Areas, which are small neighborhoods containing about 125 households each. Data weighted by student population. (1) First degree, Higher degree, NVQ levels 4 and 5, HNC, HND, Qualified Teacher Status, Qualified Medical Doctor, Qualified Dentist, Qualified Nurse, Midwife or Health Visitor, (2) households that can access at least on car or van, (3) Index as used in Census 2001, a value of 1 implies there is one room too few, (4) people per hectare, (5) Average house price: All property sales in neighborhood between 2000 and 2006 divided by monthly national average price (data source: nationwide). Student–teacher ratios in Panel C are taken from the school census, weighted by student population.

As a result I have to rely on movers to identify the effect. It is hence comforting to see that 'SH-movers' are roughly similar to 'SH-stayers' with respect to their observable characteristics, though of course not statistically identical at conventional levels. To summarize, there are differences between the 'mover' and 'stayer' groups, but it is evident that both, students who live in or move into social housing neighborhoods underperform in their KS2 and KS3 national tests.

5.4. Identifying social housing neighborhoods

Unfortunately, the school census does not contain individual-level information on housing tenure. Hence the next and crucial step is to identify who lives in a social housing neighborhood and who does not. I do this using neighborhood statistics from the 2001 Census of Population on the total number of households that rent from the council (local authority) or a registered social landlord or housing association. I combine these variables to calculate the percentage of households living in social housing for each OA. There has been very little change in the stock of social housing since 2001, and mobility is limited, as discussed in Section 4.1. As a result, it is unlikely that these neighborhoods have changed dramatically since the 2001 Census (Hills, 2007, pp. 169ff). Therefore I use the Census to identify high-density social housing neighborhoods for the entire study period. Following our identification strategy, the timing of movers into one-hundred per cent social housing neighborhoods must be exogenous, whereas movers into zero-per cent social housing neighborhoods, at the other extreme, are never constrained by social housing waiting lists. However, only very few OAs are 100 per cent social housing and many areas have a low percentage of social housing tenants. To identify social housing movers on the individual level, I choose a lower threshold of eighty per cent. If eighty per cent of all households in a particular OA live in social housing, then it is still very likely that a student who lives in that OA also lives in social housing. Therefore, everyone living in an OA with eighty per cent or more households being in social housing is treated as living in a social housing neighborhood, and all others are not. Using this threshold, by tracking OA changes over the years, it is now possible to identify those who move out of an area with less than eighty per cent of social tenants into an area with eighty per cent or more. As I already know, mobility within the social housing sector is close to zero. Hence to identify students who move into social housing I focus the analysis on those who move into an OA with more than eighty per cent of households in social housing and stay there. From now on this will be referred to as 'moving into a social housing neighborhood'.[23]

[23] In one of the robustness checks I assess the sensitivity of the results to the choice of this threshold (Section 7.2).

Table 2
Descriptive statistics for subgroups.

	(1) Student stayed in SH n'hood during study period		(2) Student moved into SH n'hood during study period		(3) Student stayed in non-SH n'hood during study period		(4) Other movers not moving into SH n'hood	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Panel A: Individual characteristics								
Key Stage 2 Score	38.156	26.840	36.720	26.636	51.271	28.851	46.922	28.460
Key Stage 3 Score	35.206	25.916	33.715	25.495	51.082	28.856	46.119	28.289
Changed school before, yr 7–9	0.038	0.191	0.095	0.293	0.019	0.135	0.083	0.276
FSME eligibility year 7	0.458	0.498	0.440	0.497	0.127	0.332	0.179	0.383
FSME eligibility year 8	0.448	0.497	0.441	0.497	0.123	0.328	0.171	0.377
FSME eligibility year 9	0.427	0.495	0.438	0.496	0.116	0.321	0.161	0.368
Gender (male = 1)	0.478	0.500	0.466	0.499	0.502	0.500	0.489	0.500
Ethnicity-White British Is.	0.599	0.490	0.655	0.476	0.828	0.378	0.796	0.403
Ethnicity-Other White	0.039	0.193	0.036	0.187	0.017	0.131	0.021	0.144
Ethnicity-Asian	0.071	0.258	0.062	0.242	0.068	0.252	0.071	0.256
Ethnicity-Black	0.183	0.387	0.150	0.358	0.030	0.172	0.046	0.211
Ethnicity-Chinese	0.007	0.085	0.006	0.080	0.003	0.057	0.003	0.056
Ethnicity-Mixed	0.047	0.211	0.040	0.195	0.024	0.152	0.027	0.162
Ethnicity-Other	0.031	0.172	0.026	0.159	0.007	0.082	0.010	0.102
Panel B: Neighborhood characteristics, pre move (if any)								
Unemployment rate	0.114	0.046	0.076	0.044	0.044	0.036	0.051	0.041
Level 4 + qualification[1]	0.498	0.112	0.563	0.130	0.625	0.130	0.611	0.131
Access to car or van[2]	0.506	0.127	0.658	0.169	0.838	0.148	0.798	0.164
Lone parent with dep. child	0.198	0.089	0.119	0.070	0.070	0.057	0.083	0.064
Limiting long term illness	0.427	0.101	0.378	0.100	0.340	0.100	0.346	0.103
Overcrowding[3]	0.205	0.133	0.136	0.115	0.065	0.076	0.079	0.087
Number of rooms	4.260	0.535	4.758	0.659	5.464	0.832	5.261	0.815
Population density[4]	139.580	160.364	86.792	80.268	52.341	49.902	60.405	61.673
Average house price[5]	0.644	0.439	0.752	0.491	0.950	0.540	0.866	0.501
Panel C: Secondary school characteristics, year 7								
Student to teacher ratio	15.659	2.038	15.732	1.924	15.791	1.716	15.841	1.764
Number of students	*16,497*		*3092*		*856,350*		*187,496*	
Number of neighborhoods (year 7)	*2190*		*2699*		*104,449*		*79,215*	
Number of schools	*1229*		*1017*		*2431*		*2250*	

Notes: Rows: Panel A: Key Stage 2 (Key Stage 3) is the national assessment at age 11 (14) percentalised at cohort-subject level. FSME is free school meal eligibility. Panel B shows data from the 2001 UK Census Output Areas, which are small neighborhoods containing about 125 households each. Data weighted by student population. (1) First degree, Higher degree, NVQ levels 4 and 5, HNC, HND, Qualified Teacher Status, Qualified Medical Doctor, Qualified Dentist, Qualified Nurse, Midwife or Health Visitor, (2) households that can access at least on car or van, (3) Index as used in Census 2001, a value of 1 implies there is one room too few, (4) people per hectare, (5) Average house price: All property sales in neighborhood between 2000 and 2006 divided by monthly national average price (data source: nationwide). Student–teacher ratios in Panel C are taken from the school census, weighted by student population.

5.5. Descriptive statistics for social housing neighborhoods

Table 3 shows descriptive statistics for all neighborhoods that appear in at least one of the years and cohorts, split into non-social housing and social housing using the above definition. What becomes evident is that high-density social housing neighborhoods are among the most deprived areas in England. The average unemployment rate of a high-density social housing neighborhood, for example, is worse than the unemployment rate of the 95th percentile of non-social housing neighborhoods. To summarize, these high-density social housing neighborhoods are among the most deprived neighborhoods in England, at least in terms of observable census characteristics.

In my final dataset 3092 students move into such social housing neighborhoods between their seventh and eleventh academic year. 1023 students move into social housing from year seven to eight, 758 from year eight to nine, 616 from year nine to ten and 695 between the academic years ten and eleven.[24] Table 4 looks explicitly at the neighborhood-level changes that the students who move into social housing neighborhoods experienced (now weighted by student numbers). We can see that neighborhood quality deteriorates in all characteristics for students who move into a social housing neighborhood. Students who move into a social housing neighborhood move into a neighborhood with a fifty-three per cent higher unemployment level, fifteen per cent lower qualification levels, twenty-four per cent lower access to a car or van, and fifty-eight per cent more lone parents with dependent children. Furthermore, their new neighborhoods have seventeen per cent more inhabitants with limiting long-term illness, a thirty per cent higher overcrowding index, ten per cent fewer rooms in the average household, twenty-two per cent higher population density, and twenty-one per cent lower house prices. The third column of Table 4 expresses these changes in terms of standard deviations. Overall, the changes experienced by social housing movers are substantial; they vary between a third to one standard deviations changed in the underlying variables. Note that what this study identifies is this aggregate effect on school results that arises from this general deterioration in neighborhood quality, measured by $D(SH)_{i,t-1,t}$ in order to proxy for $(\mathbf{Z}_{nt} - \mathbf{Z}_{nt-1})$ in the equations in Section 3.

6. Results

6.1. 'Traditional'/OLS approach

Before I turn to the main results, it is useful to inform the discussion with some benchmark regressions. These regressions are for comparative purpose only and do not focus on identification: they simply correlate KS3 results with the areas where the students live or move to.

Table 5 shows the results from these regressions and is organized into two panels with three regressions each, where addi-

[24] Numbers are slightly higher for the earlier years, but this merely reflects the general decline in mobility and is not social housing neighborhood specific.

Table 3
Social housing neighborhoods, descriptive statistics.

	Mean	s.d.	p5	p25	p50	p75	p95
Not Social Housing							
Unemployment rate	0.043	0.037	0	0.023	0.035	0.059	0.115
Level 4 + qualification	0.635	0.135	0.405	0.538	0.641	0.735	0.850
Access to car or van	0.832	0.154	0.517	0.741	0.885	0.957	1
Lone parent with dep. child	0.063	0.052	0	0.028	0.049	0.084	0.170
Limiting long term illness	0.334	0.104	0.173	0.261	0.328	0.402	0.517
Overcrowding	0.066	0.076	0	0.023	0.040	0.085	0.231
Number of rooms	5.394	0.911	4.010	4.790	5.310	5.910	7.070
Population density	49.804	47.827	0.583	17.632	43.160	67.921	128.620
Average house price	1.015	0.642	0.328	0.605	0.886	1.246	2.139
Social Housing							
Unemployment rate	0.117	0.052	0.043	0.082	0.113	0.147	0.210
Level 4 + qualification	0.471	0.120	0.279	0.379	0.471	0.560	0.664
Access to car or van	0.472	0.126	0.283	0.386	0.464	0.550	0.701
Lone parent with dep. child	0.160	0.089	0.025	0.096	0.155	0.218	0.316
Limiting long term illness	0.451	0.110	0.277	0.370	0.448	0.527	0.642
Overcrowding	0.183	0.125	0.043	0.084	0.136	0.281	0.415
Number of rooms	4.119	0.538	3.350	3.720	4.050	4.500	5.060
Population density	119.226	141.273	15.235	46.570	76.717	145.622	347.676
Average house price	0.588	0.441	0.156	0.299	0.485	0.801	1.188

Notes: Based on the main sample from column 4 of Table 1. All neighborhoods included that have at least one student in at least one observation year. Number of neighborhood observations: 121,482, of which 2194 are social housing. For variable definitions see notes of Table 1.

tional controls and school fixed effects are added subsequently in columns (1)–(3) and (4)–(6).

Panel A shows estimates for the effect on KS3 scores of living in a social housing neighborhood at the start of secondary education (year 7). Without further controls, the estimate in the first row shows that students who lived in social housing neighborhoods in year 7 score 14.6 percentile points lower than their peers. This is an extremely strong association; it is hence not surprising that educational underperformance has been linked to neighborhood quality in the past. However, this association between place and test score reduces to about 2.8 percentile points once a rich set of controls including prior KS2 results are added (column 2). With school fixed effects, this association reduces further to 1.5 points, while remaining statistically significant at the one-percentage level (column 3). Note that variables such as the number of years of free school meal eligibility – an income proxy – are more important in determining school improvements.

In panel B the effect is estimated for students who move into social housing neighborhoods before the test in year 8 and 9. This is Eq. (1) from Section 3. The unconditional association is now −12.5 percentile points (column 4) and it again reduces substantially, to two percentile points, once additional controls (column 5) and to 0.9 percentiles points once school fixed effects (column 6) are added, all statistically significant at the one per cent level. Notably, the estimates in pane B are quite similar to panel A. If anything, the associations between moving into a social housing neighborhood and the test results are somewhat weaker compared to those who lived in social housing in year 7. I believe that it is interesting and relevant to observe that social housing movers and students growing up in social housing both underperform in a roughly similar way. However, I clearly note that this study identifies effects of moving into high-density social housing and can say very little about longer-term effects, which I discuss further in the conclusion.

Table 4
Neighborhood quality treatment.

	(a) New SH n'hood	(b) % ch.	(c) S.D. ch.
Unemployment rate	0.118	53.25	0.932
Level 4 + qualification	0.478	−15.10	−0.659
Access to car or van	0.502	−23.71	−0.934
Lone parent with dep. child	0.189	57.50	0.972
Limiting long term illness	0.440	16.71	0.630
Overcrowding	0.175	29.63	0.357
Number of rooms	4.294	−9.73	−0.713
Population density	115.035	31.90	0.343
Average house price	0.583	−21.32	−0.330

Notes: 3092 students in 2699 neighborhoods. This is the subgroup described in column (2) of Table 2. Neighborhood-variables defined as described in notes of Table 1.

6.2. Main results: early and later movers into social housing neighborhoods

6.2.1. The unconditional difference-in-difference estimator

Table 6 derives the unconditional DiD-estimator. This table shows descriptive statistics (means) for groups moving before KS3/after KS3 and into social housing/non-social housing neighborhoods. Students who move into a social housing neighborhood before the test have average KS3 scores of 34.198, students who moved during the two years after the test score on average 33.068 (column 1). The corresponding figures for non-social-housing neighborhood movers are 46.712 and 45.417, as shown in column (2). In column (3) the first differences are shown for students either moving before or after the KS3 test. Students who move into social housing before the KS3 score 12.515 points worse than students who move between non-social-housing neighborhoods. Note that this simple difference in means is equivalent to the unconditional OLS-estimate presented in Table 5 column (4). In the last column of Table 6 I difference the first differences again, which results in the unconditional difference-in-differences of −0.165 KS3 points for students moving into social housing before versus after the test. This is equivalent to the estimate shown in the first column of Table 7.

6.2.2. Main results

Table 7 shows the estimates for Eq. (7) discussed in Section 3. Column (1) shows the unconditional estimate only controlling for a potential direct effect of moving, column (2) additionally includes previous test scores, ethnicity, school characteristics and gender, and in column (3) school fixed effects are added to the specification. In column (4) school fixed effects are replaced with

Table 5
Social housing and school performance, OLS.

	Panel A			Panel B		
Dependent variable: KS3	(1)	(2)	(3)	(4)	(5)	(6)
Lived in SH neighborhood in year 7	−14.6337 (0.231)**	−2.814 (0.148)**	−1.462 (0.124)**	–	–	–
Moved into SH n'hood before KS3 test	–	–	–	−12.515 (0.624)**	−2.052 (0.362)**	−0.894 (0.339)**
Key Stage 2 score	–	0.851 (0.000)**	0.823 (0.001)**	–	0.852 (0.000)**	0.823 (0.001)**
Changed secondary school before KS3	–	−2.492 (0.087)**	−0.831 (0.092)**	–	−2.667 (0.088)**	−0.981 (0.092)**
FSME eligibility year 7	–	−2.709 (0.074)**	−1.732 (0.070)**	–	−2.770 (0.074)**	−1.756 (0.070)**
FSME eligibility year 8	–	−1.303 (0.088)**	−0.745 (0.084)**	–	−1.334 (0.088)**	−0.756 (0.084)**
FSME eligibility year 9	–	−1.910 (0.077)**	−1.197 (0.074)**	–	−1.946 (0.077)**	−1.206 (0.074)**
Gender (male==1)	–	−1.517 (0.028)**	−1.329 (0.028)**	–	−1.516 (0.028)**	−1.330 (0.028)**
Student to teacher ratio y. 7	–	−0.393 (0.011)**	0.018 (0.016)	–	−0.391 (0.011)**	0.018 (0.016)
Control for moving into SH	No	No	No	No	No	No
Controls for moving	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity-controls	No	Yes	Yes	No	Yes	Yes
School fixed effects	No	No	Yes	No	No	Yes
Number of student observations	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*

Notes: Neighborhoods classified as Social housing if at least 80% of residents in social rented sector. SH movers who move only once. Only students who always lived in Local Authority with more than 5% of population on Social Housing waiting list. This sample corresponds to column (4) in Table 1. Columns (3) and (6) include 2442 school fixed effects. Standard errors clustered at the neighborhood-level in shown parenthesis.
** Sig. at 1%.

Table 6
Constructing the DID estimator.

Dependent variable: KS3 test scores	(1) Moved into SH n'hood	(2) Moved into non-SH n'hood	(3) First Difference	(4) DiD
Move before KS3 test	34.198	46.712	−12.515	−0.165
Move after KS3 test	33.068	45.417	−12.350	

Notes: These are the mean differences, corresponding to column (1) of Table 7. Mean differences in percentalized KS3 test scores. Sample is described in column (4) of Table 1 and in Table 2.

neighborhood fixed effects and the final column controls for neighborhood and school fixed effects simultaneously.[25]

The first row shows estimates for moving into a social housing neighborhood before the test γ_1, which are now statistically non-significant at conventional levels in all specifications. The simple mean-difference-in-difference of −0.165 in column (1) is not statistically significantly different from zero. Adding controls, this causal estimate of moving into social housing before the KS3 test even turns positive in columns (2)–(5), and is estimated at 0.679, 0.630, 0.752 and 0.754 respectively. However, none of these estimates is statistically significantly different from zero at conventional levels. This result is in contrast to the cross-sectional estimates presented in Table 5. Importantly, it is not driven by increases in the standard errors but by actual changes of the estimated coefficients.[26] Although students who move into a social housing neighborhood before the KS3 test underachieved, they did not underachieve to any different degree compared to their peers who move into a similar neighborhood after the KS3 test.

This becomes directly evident when comparing these results with OLS estimates. For example, column (4) from Table 5 gives a negative association of 12.515 percentile points for early SH-movers. In Table 7, this association is now fully captured by the dummy variable that controls for moving into social housing before or after the test $D(SH)_{i,t-1,t+1}$, which is estimated at −12.350 in column (1). This strongly suggests that the previous negative associations between test scores and moving into social housing neighborhoods are driven by unobservable characteristics common among all students who move into social housing neighborhoods at some point (denoted by ϕ_g in Section 3), and not at all by exposure to social housing neighborhoods.

These conclusions are further substantiated in column (4), which includes neighborhood destination fixed effects. Here, the estimate in the first row shows the difference in KS3 results for students who moved into the same social housing neighborhood before or after the test. Again, there is no evidence for detrimental effects on test scores. This is an important finding because the neighborhood fixed effect absorbs any constant selection of groups or individuals into specific social housing neighborhoods, as well as for potential institutional discrimination. The final column shows that additionally controlling for school fixed effects results in an almost identical coefficient, which is why the specification of column (4) will be used for benchmarking purposes in the subsequent sections.

Whenever arguing for zero- or non-negative effects one has to carefully examine the precision of the estimates. In this case, the most negative value that is still within the 95-per cent

[25] Estimated using the STATA routine reg2hdfe (Guimaraes and Portugal, 2010).
[26] I cluster standard errors at the neighborhood level. Using robust standard errors instead does not alter any of the conclusions.

Table 7
Main results: social housing and school performance DID.

Dependent variable: KS3 test scores	(1)	(2)	(3)	(4)	(5)
Move into SH neighborhood before KS3 test	−0.165	0.679	0.630	0.752	0.754
	(0.939)	(0.538)	(0.512)	(0.555)	(0.539)
Move into SH neighborhood before or after KS3 test	−12.350	−2.735	−1.528	0.308	−0.006
	(0.720)**	(0.406)**	(0.385)**	(0.437)	(0.420)
Key Stage 2 score	–	0.852	0.823	0.832	0.817
		(0.001)**	(0.001)**	(0.001)**	(0.001)**
Changed secondary school before KS3	–	−2.666	−0.980	−2.126	−1.041
		(0.088)**	(0.092)**	(0.092)**	(0.099)**
FSME eligibility year 7	–	−2.767	−1.755	−1.293	−1.157
		(0.074)**	(0.070)**	(0.076)**	(0.074)**
FSME eligibility year 8	–	−1.334	−0.756	−0.605	−0.463
		(0.088)**	(0.084)**	(0.091)**	(0.089)**
FSME eligibility year 9	–	−1.942	−1.204	−0.915	−0.803
		(0.077)**	(0.074)**	(0.080)**	(0.079)**
Gender (male==1)	–	−1.516	−1.330	−1.563	−1.364
		(0.028)**	(0.028)**	(0.029)**	(0.030)**
Student to teacher ratio, year 7	–	−0.391	0.018	−0.344	−0.006
		(0.011)**	(0.016)	(0.012)**	(0.017)**
Control for moving into social housing	Yes	Yes	Yes	Yes	Yes
Controls for effects of moving	Yes	Yes	Yes	Yes	Yes
Ethnicity-controls	No	Yes	Yes	Yes	Yes
School fixed effects	No	No	Yes	No	Yes
Output Area fixed effects (after move)	No	No	No	Yes	Yes
Number of student observations	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*

Notes: Neighborhoods classified as Social housing if at least 80% of residents in social rented sector. SH movers who move only once. Only students who always lived in Local Authority with more than 5% of population on Social Housing waiting list. This sample corresponds to column (4) in Table 1. Columns (3) and (5) include 2442 school fixed effects. Columns (4) and (5) include 109,868 (year-11) neighborhood fixed effects. Column (5) is estimated using STATA-Command "red2hdfe" with a tolerance of 0.001 (Guimaraes and Portugal, 2010). Errors clustered at neighborhood level and shown in round parenthesis.
** Sig. at 1%.

confidence interval of the estimate in column (4) is $0.752 - (1.96)^{*}0.556 = -0.338$, which corresponds to about 1.2 per cent of a KS3 standard deviation. This is an extremely small effect.

To summarize the results, the traditional approach results in statistically significant negative associations between living in or moving into social housing neighborhoods, and schooling. These associations persist despite the inclusion of a rich set of control variables. However, the difference-in-difference results show that these negative associations are entirely driven by characteristics common to students who move into these neighborhoods at some point, and not by neighborhood exposure before taking the test. Using the timing of a move as a source of exogenous variation, there is no evidence for detrimental short-term effects from moving into a deprived social housing neighborhood.

6.3. Subject-heterogeneity

So far we have only considered effects of moving into highly deprived neighborhoods on aggregate test score measures. Table 8 shows results for English, Mathematics and Science separately. Summary statistics of these variables are very similar to the overall KS2 and KS3 scores described in Tables 1 and 2 by construction, since the latter are based on averages of the former cohort-subject percentalized national scores. As a result, all of these scores average very close to fifty in the final sample.

Interestingly, the effect on English test scores is positive and estimated at 1.278 national percentile points, though only weakly significant at the 10 per cent significance level, whereas the estimates for mathematics and science are closer to zero. However, I cannot reject the null hypothesis that the coefficients are all equal at conventional levels. Previewing some of the findings reported in the next section, I nevertheless investigate this further and test if results by subject differ depending on a student's gender. However, in these specifications none of the estimated effects of moving into social housing, including on English scores, turns out significant for either gender. My overall reading of these additional results is that negative short-term effects are extremely unlikely and that these results support the main conclusion. The following section tests for further interactions.

6.4. Gender, schools and neighborhood interactions

Table 9 shows estimates of specifications that allow for various interactions to examine if moving into social housing matters when combined with other characteristics or changes.[27] In column (2) I split the treatment by gender to allow for the possibility that boys and girls experience different effects. This is motivated by some of the recent literature finding gender differences in neighborhood effects. Kling et al. (2005), for example, find different neighborhood effects for female and male youth on criminal activity. I find a positive interaction effect for boys of 0.062, suggesting no significant gender differences.

Columns (3) and (4) consider if the effect varies depending on school-level interactions. Column (3) presents results for a regression that allows for a different treatment effect for students who move into a social housing neighborhood and also change secondary school. It is possible that lower neighborhood quality only matters if the school environment changes as well. If this was the case, then there should be statistically significant differences between those two groups. Indeed, the estimate for the interactions

[27] Note that when allowing for interaction effects in my difference-in-difference framework interactions need to be included for all relevant group variables. Therefore all regressions presented in Table 9 include main interaction effects and interactions with the general moving dummies as well. This means that for each specification five additional terms are added: one main effect (which is absorbed by the Output Area FX), two in interaction with the general moving dummies, and two further interactions that are social-housing-move specific. In Table 9, I only report the coefficients for the interactions with the social housing move, which are of main interest.

Table 8
Results by subject.

	(1) Benchmark	(2) English	(3) Mathematics	(4) Science
Move into SH neighborhood before KS3 test	0.752	1.280	0.358	0.476
	(0.556)	(0.679)$^+$	(0.572)	(0.706)
Move into SH neighborhood before or after KS3 test	0.308	0.485	0.007	0.879
	(0.437)	(0.544)	(0.456)	(0.550)
Number of student observations	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*

Notes: Benchmark is column (4) from Table 7. The outcome variables are the national age-14 test scores percentalised at the subject-cohort level. All regression control for subject specific KS2 scores and the same individual controls as before, controls for moving into social housing, controls for direct effects of moving and 109,868 (year-11) output area fixed effects. Neighborhoods classified as Social housing if at least 80% of residents in social rented sector. SH movers who move only once. Only students who always lived in Local Authority with more than 5% of population on Social Housing waiting list. Errors clustered at neighborhood level. Standard errors in brackets. + sig. at 10%.

Table 9
Testing for the nature of the effect, interactions.

Dependent variable: KS3 test scores	(1) Baseline	(2) Gender (male = 1)	(3) Changed School before KS3	(4) Change in n'hood school peers	(5) Change in n'hood % unemp't.	(6) Change in n'hood % lone parents
Interaction * Move into SH n'hood before KS3	–	0.062	2.642	−0.227	0.183	0.052
		(1.102)	(2.323)	(0.317)	(0.084)*	(0.050)
Interaction* Move into SH n'hood before or after KS3	–	0.528	−1.426	0.328	−0.181	−0.056
		(0.841)	(2.044)	(0.257)	(0.071)*	(0.039)
Move into SH neighborhood before KS3	0.752	0.777	0.512	0.601	0.132	0.557
	(0.555)	(0.774)	(0.577)	(0.582)	(0.647)	(0.660)
Move into SH neighborhood before or after KS3	0.308	0.045	0.389	0.520	0.312	−0.273
	(0.437)	(0.606)	(0.444)	(0.460)	(0.515)	(0.529)
Number of student observations	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*	*1,063,435*

Notes: Baseline regressions is Table 7 (column 4). Interaction main effects and for non-SH movers always included (coefficients not reported here). Neighborhoods classified as social housing if at least 80% of residents in social rented sector. Movers only move once. Only students who always lived in Local Authority with more than 5% of population on Social Housing waiting list. Over 1 m obs., errors clustered at neighborhood level. Standard errors in brackets.
** Sig. at 1%.
* Sig. at 5%.

between changing school and moving into social housing before the KS3 test is positive at 2.64 percentile points (first row). However, the standard error is very large and this estimate is not statistically significant.[28] Next, in column (4) I interact the treatment with the absolute difference in school-peers in the local neighborhood. Here, I compute the number of neighbors who attend the same school before and after moving and interact this with the moving indicator, thus testing if effects are larger if there are more school peers in the new neighborhood. This does not seem the case.

Finally, we estimated effects of general deteriorations in neighborhood quality along numerous dimensions (as described in Section 5.5). The results so far suggest that there is no overall effect on KS3 test scores of these combined 'neighborhood-treatments'. However, this finding does not preclude the possibility that individual dimensions of this composite measure have an effect. Here, I consider interactions with changes in the neighborhood level unemployment rate (column 4) and the change in the percentage of lone parents with dependent children (column 5). The point estimates in the first row show if moving into social housing neighborhoods before the test has a differential impact on test scores depending on changes in neighborhood unemployment and shares of lone parents, where a positive change indicates increases in these rates. The estimate in column (5) is statistically significant at the 5% level but has the wrong sign: students moving into social housing before the test do 0.138 points better for each additional percentage point in the deterioration in the neighborhood unemployment rate they experienced. In addition, this point estimate as well as its statistical significance are very sensitive to controls and the type of fixed effects used. Next, interacting movers by changes in shares of lone parents (column (6)) does not result in statistically significant estimates. Since students moving into social housing experiences large deteriorations in other neighborhood indicators as well, I also estimated coefficients for interactions with all further neighborhood variables listed in Table 4. However, the estimates of these additional interactions with the social housing movers remain very close to zero or statistically insignificant. The coefficients change size and signs depending on the chosen specification, but never get statistically significant at conventional levels. Overall, these results confirm the previous conclusions that there is no evidence for negative short-term neighborhood effects for teenagers moving into social housing.

7. Assessing the identification strategy

7.1. Balancing

7.1.1. Balancing of individual and neighborhood characteristics: graphic analysis

The identifying assumption of this study is that early and late movers into social housing neighborhood follow common trends. If early and late movers had different characteristics, this could potentially confound the analysis that links differences in exposure-times to social housing neighborhoods to school performance.

The data allows me to address this concern directly, at least regarding observable characteristics. Fig. 3 shows averages of individual characteristics and neighborhood change for students moving into social housing neighborhoods, by year. The left-hand side shows the percentage of students who were eligible for free school meals in year 7, their gender and KS2 result. Notably, all these

[28] Including school fixed effects moves this estimate closer to zero in magnitude (−0.66), remaining insignificant at any conventional level.

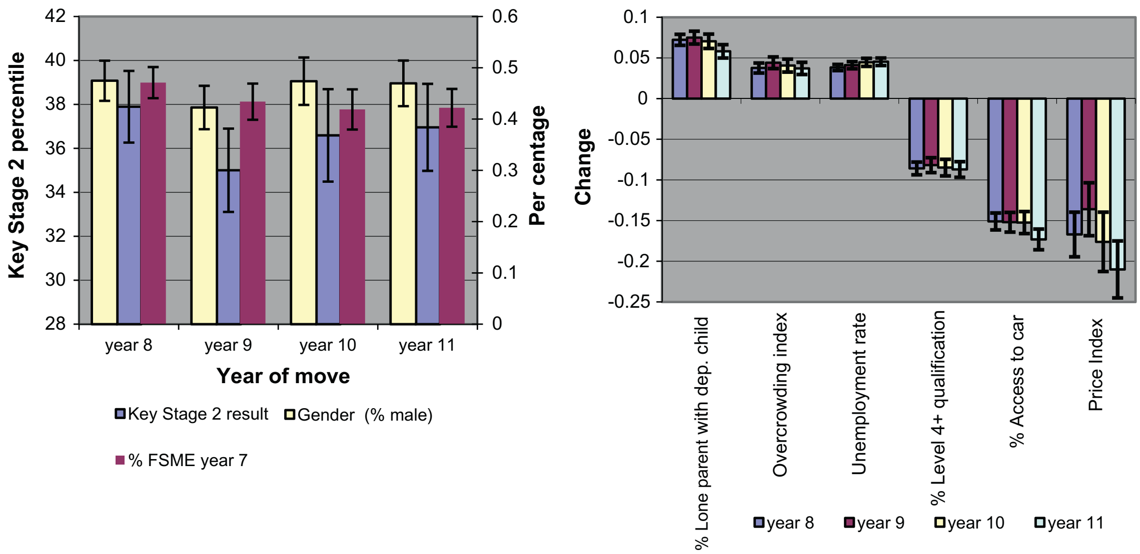

Fig. 3. Balancing of students and neighborhoods by year of move.

characteristics are determined before anyone moves and cannot be endogenous to the quality of the new neighborhoods. The figure clearly shows that students who move into social housing neighborhoods are very similar across the years.

The right-hand side displays whether changes in neighborhood quality differ depending on the year of the move. I would expect the change in neighborhood quality (the underlying treatment) to be balanced with respect to the year of moving into a social housing neighborhood. Again, regardless of the year of relocation, students move into neighborhoods with similarly larger percentages of lone parents, more overcrowding, higher unemployment rates, lower qualification levels, lower access to cars and lower house prices.

7.1.2. Balancing of individual and neighborhood characteristics: probit analysis

While the graphical analysis is reassuring, we can also test whether early movers differ from post-KS3 test movers into social housing neighborhoods formally using a probit regression and Maximum Likelihood. Table 10 presents marginal effects-estimates using the 3092 students who move into social housing at some point where the dependent variable equals one if the student moves before the KS3 test. All available individual and neighborhood characteristics are entered as explanatory variables.

If the identification assumption is violated, the KS2 score which correlates highly with the KS3 should be particularly prone to picking up differences between early and late movers. But as we can see from the marginal effects estimates in the second row of column (1), early and late movers into social housing are literally identical with respect to previous attainment. This difference is estimated at 0.000364 and not statistically significant. The fact that the KS2 results of early and late movers look extremely balanced is therefore particularly comforting. Notice that similar conclusions hold for the other pre-determined variables like free school meal eligibility in year 7, gender or ethnicity, as shown by the remain estimates in column (1), as well as neighborhood characteristics with the one exception of the overcrowding index, which is significant at the five per cent level. For three of the four cohorts, we can further test the common trends assumption using much earlier age-7 Key Stage 1 test scores, which are estimated separately. This is particularly interesting in our setting because families who move into social housing earlier than others must have joined to waiting lists earlier compared to families moving later. Still, we cannot detect meaningful differences.

The second column presents estimates for 4444 students who moved out of social housing during the study period. I have so far not explicitly focused on these students in the analysis because there are fewer reasons to believe that the timing of moving out of social housing could be exogenous. Essentially, this is because there are no waiting lists for moving out of social housing. However, even for these students, I cannot predict the year of move using a rich set of background variables including prior KS1 and KS2 test scores. Finally, the third column shows that even non-social-housing neighborhood movers are quite balanced with regard to the timing of the move. For this group, there is a highly statistically significant relation between both KS1 and KS2 test scores and the timing of the move, but the marginal effects are extremely small, estimated at 0.000232 and 0.000539. This means that each additional point in the KS2 test, for example, makes moving early 0.02 per cent more likely. This regression is estimated using over 183,052 students who move once and between non-social-housing neighborhoods during the study period, of which about fifty-six per cent actually move before the KS3. In other words, early non-social-housing neighborhood movers do very marginally better in terms of pre-determined KS2 test scores, than late movers. Notice that this biases toward finding negative neighborhood effects for the social housing movers in the difference-in-difference framework, which is not what we find.

As discussed, another important assumption for the validity of the difference-in-difference approach is that there are no direct income effects resulting from moving into social housing. To test for this directly, Table 10 also includes indicators for the free school meal status in the academic years 7 and 8 as regressors (second and third rows). These estimates are not statistically significantly different to zero for the social housing movers. This means that even free school meal eligibility in years 8 and 9, which are not a pre-determined measures for the early movers, fail to predict the timing of the move for social housing neighborhood movers (column 1). In other words, the time-sensitive free school meal indicator does not show any reaction to moving into social housing, which is comforting and in line with expectations (see Appendix A1).

To conclude the discussion, in the last row I test the hypothesis that all coefficients jointly equal zero. It turns out that in columns

Table 10
Probability of moving in the two years before versus after the KS3 test.

	(1) Moving into SH n'hood		(2) Moving out of SH n'hood		(3) Non-SH n'hood move	
Key Stage 1 score (age-7)[1]	−0.000124	(0.15)	0.0000225	(0.03)	0.000232*	(2.08)
Key Stage 2 score (age-11)	0.000364	(0.42)	−0.0000274	(0.04)	0.000539**	(5.02)
FSME eligibility year 7	−0.0378	(0.54)	0.0544	(0.91)	0.0275*	(2.14)
FSME eligibility year 8	0.119	(1.50)	0.00732	(0.10)	0.00255	(0.16)
FSME eligibility year 9	0.0656	(0.81)	−0.118	(1.59)	−0.0641**	(3.94)
FSME eligibility year 10	−0.00545	(0.07)	−0.0109	(0.14)	−0.00237	(0.14)
FSME eligibility year 11	0.00982	(0.13)	0.00667	(0.10)	0.0232	(1.58)
Gender (male==1)	−0.0466	(1.02)	−0.0402	(1.06)	0.0282**	(4.77)
Ethnicity-White British Isles	0.0892	(0.59)	−0.0748	(0.58)	−0.0249	(1.30)
Ethnicity-Other White	0.220	(1.13)	−0.110	(0.65)	0.0105	(0.37)
Ethnicity-Asian	0.160	(0.90)	−0.0754	(0.52)	0.0258	(1.15)
Ethnicity-Black	0.152	(0.93)	−0.167	(1.23)	−0.0161	(0.66)
Ethnicity-Chinese	0.212	(0.71)	−0.175	(0.67)	0.00595	(0.10)
Ethnicity-Mixed	0.0543	(0.29)	−0.114	(0.73)	−0.0527*	(2.01)
Ethnicity-Other	0.243	(1.17)	−0.0388	(0.21)	−0.00641	(0.18)
Teacher to student ratio (y7)	−0.000491	(0.04)	0.00566	(0.56)	−0.00396*	(2.32)
Cohort	−0.0223	(1.03)	−0.0344	(1.93)	−0.0327**	(11.73)
Unemployment rate	0.773	(1.14)	−0.377	(0.89)	0.276*	(2.52)
Level 4 + qualification	0.144	(0.47)	0.656*	(2.23)	0.203**	(5.05)
Access to car or van	0.188	(0.80)	−0.363	(1.85)	−0.0697	(1.84)
Lone parent with dep. child	0.308	(0.79)	−0.364	(1.30)	−0.180**	(2.77)
Limiting long term illness	−0.182	(0.50)	0.115	(0.40)	−0.0377	(0.80)
Overcrowding	−0.823*	(2.37)	−0.363	(1.48)	−0.0998	(1.71)
Number of rooms	−0.0741	(1.34)	−0.0453	(0.77)	−0.0437**	(7.78)
Population density	0.000245	(0.67)	−0.000353*	(2.51)	−0.0000500	(0.75)
Average house price	−0.0882	(1.12)	−0.108	(1.44)	−0.0163	(1.61)
School FX	No		No		No	
Number of student observations	3092		4444		183,052	
H0: All coefficients equal zero. Prob > chi2	0.556		0.383		0.000	

Notes: Dependent variable equals one if a student moves before KS3 in sample where everyone move once and into Social Housing neighborhoods, hence either before or after KS3. Probit regression, marginal effects. Standard errors in brackets and clustered at neighborhood level. Only students who always lived in Local Authority with more than 5 per cent of population on Social Housing waiting list included. Note 1: Key Stage 1 coefficients are estimated in a separate regression including all covariates but only using a smaller sample because these age-7 results are not available for the first cohort. *z*-Scores in parenthesis.
* Sig. at 5%.
** Sig. at 1%.

(1) and (2) we fail to reject the null for the social housing neighborhood movers. However, for non-social-housing neighborhood movers I can reject the null of joint insignificance, although the estimated coefficients are not very dissimilar in terms of magnitude. Given these results, I therefore cannot completely rule out the possibility that social housing neighborhood movers *look* balanced partly due to large standard errors. Notice, however, that these balancing test are unconditional on school and neighborhood fixed effects.

7.1.3. Balancing: OLS with fixed effects

To investigate this possibility further I run additional balancing regressions where I can also include school fixed effects. This can be done by running balancing regressions where individual characteristics (in particular the KS2 test scores) are used as dependent variable and predicted by the timing of the move. This setup then allows us to keep the whole sample, including students who do not move, which in turn makes it possible to correctly estimate school fixed effects.

Table A3 reports estimates for such balancing regressions that use the KS2 test score as dependent variable. Column (1) and (3) report estimates for social-housing-neighborhood movers, while columns (2) and (4) focus on non-social-housing neighborhood moves, and columns (3) and (4) include school fixed effects. The estimates reported in column (3) come from the following specification:

$$y_{ignsct-1} = \kappa_1 D(SH)_{i,t-1,t} + \kappa_2 D(SH)_{i,t-1,t+1} + \mathbf{S}'\boldsymbol{\kappa} + c_c + \varepsilon_{ignsct} \qquad (8)$$

where $y_{ignsct-1}$ is the KS2 test result and the matrix $\mathbf{S}$ denotes dummy variables for each secondary school at enrollment in the academic year 7. The reported results show that using the timing of the move as independent variable, OLS regressions on KS2 scores are not statistically significant for SH-movers but again significant for non-SH movers. As before the signs are reversed, clearly indicating that SH-movers are different to other movers at least with regard to the timing of moving. Once school fixed effects are included (columns (3) and (4)), the coefficient for moving into social housing neighborhoods before the KS3 remains statistically insignificant and gets closer to zero, whereas the coefficient for non-SH-before-KS3-moves stays statistically significant and does not change much in size (0.671–0.622). Again, I read these results as supporting the identification assumption that the timing of SH-moves is quasi-exogenous for social housing neighborhood movers, and in fact different to the timing behavior of non-social-housing neighborhood students. Of course, there might still be unobserved differences between these groups, but if unobservable characteristics positively correlate with observable characteristics (see Altonji et al., 2005), then these balancing regressions can be interpreted as providing indirect evidence of the validity of the identification assumption.

7.2. Identifying social housing neighborhood movers

A data limitation of this study is that I am unable to exactly identify students who move into social housing neighborhoods. Instead, I need to rely on Output Area information from the UK 2001 Census of Population to determine if a neighborhood is social housing or not, as explained in Section 5.4. Since only a handful of neighborhoods have one-hundred per cent social tenants, all OAs with at least eighty per cent social tenants were classified as social

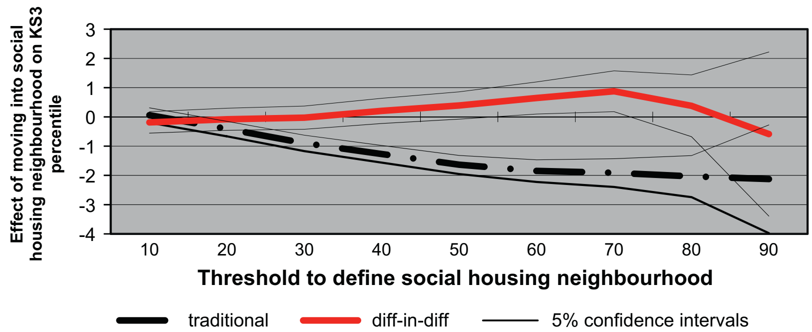

Fig. 4. Changing the threshold of the social housing neighborhood definition.

housing neighborhoods. Note that neighborhood quality is negatively correlated with the threshold level. Neighborhoods with at least twenty per cent social tenants are worse than neighborhoods with at least ten per cent social tenants, but better than those with at least thirty per cent regarding the various neighborhood characteristics. I impose this somewhat arbitrary threshold to focus on students who move into neighborhoods with at least eighty per cent of social renters. This means that someone who moves from a neighborhood with seventy-nine per cent social renters to one with eighty-one per cent is now coded as 'moving into social housing'.

In order to test if the choice of the threshold level influences the findings is to run separate regressions for different cut-off points. The sensitivity of the main result to the definition of this threshold is shown in Fig. 4. The dashed black line plots the estimates for the 'traditional' control strategy and the solid line for the difference-in-difference estimates. First, we can clearly see that the estimated negative neighborhood effect becomes larger as we increase the threshold in the 'traditional' approach. The estimated effect of moving from a neighborhood with less than ten per cent social tenants to a neighborhood with at least ten per cent is close to zero but increases quickly in size and significance, shifting the threshold level up. The DID estimate, on the other hand, remains constant around zero, or even weakly positive, suggesting that there is no negative neighborhood effect regardless of the definition of the threshold. This suggests that the increasing negative effects in the 'traditional' estimates reflect unobserved characteristics that correlate negatively with KS3 results and neighborhood quality. This is in line with the main finding that the negative association between neighborhood quality and school results disappears once controlling for moving into the social housing neighborhood at some point.

Finally, rather than just changing around the threshold of social housing tenants itself, I can further classify high-density social housing neighborhoods by their remaining share of owner occupiers. This is interesting for the following reason: high-density social housing neighborhoods with low share of owner occupation have higher shares of private rented accommodation. The skeptical reader might worry that if mobility is a lot higher in the private rented sector, then I might just pick up private movers into the remaining private rental market in high-density social housing neighborhoods rather than actual social housing movers. I can partly address this concern by focusing on high-density social housing neighborhoods that have a low remaining share of private rental, i.e. a high remaining share of owner occupation. Neighborhoods that have at least eighty per cent social tenants have remaining shares of owner occupation that vary between zero and twenty per cent. The median is at about nine per cent owner occupation, the seventy-fifth percentile at about twelve per cent, the ninetieth percentile at fourteen and ninety-fifth percentile at sixteen per cent owner occupation. I use this information to recode the treatment variables and only assign "moving into social housing" if that neighborhood has a social rental share of over eighty per cent and at the same time an owner occupation share above the median, seventy-fifth, ninetieth and ninety-fifth percentile. To re-iterate, the idea is that excluding movers who move into high-density social housing neighborhoods with very high owner occupation rates leaves very little room for private renters to cause the mobility patters that I see in the data. This is because the private rental market is very small in these neighborhoods. Makings these modifications I re-estimate all specifications of Table 7. Of the resulting sixteen coefficients only two turn out marginally statistically significant at the five per cent level, but these are positive. However, none of the estimates corresponding the most robust specification, i.e. including neighborhood fixed effects, is statistically significant.[29] I therefore conclude that it is highly unlikely that movers in the private sector in neighborhoods with high social tenancy shares affect the interpretation of my results.

7.3. Different control groups

The interpretation of my results hinges on believing that Eq. (7) identifies a suitable control group for students moving into highly deprived social housing neighborhoods. In the following, I examined two modifications of the control group, which both seem plausible but do not turn out changing my conclusions.

First, I consider the case where I only focus on students changing their neighborhoods but not their schools. In particular, we do not want to compare local movers into social housing against general movers who might move very for and for different reasons. Note that we have already examined possible interactions between the school and neighborhood domains in Section 6.4 and tested if neighborhood effects might exist (or differ) for students who also change their schools. This might be because of school-neighborhood interaction effects or because movers who do not change schools do not more very far in a geographical sense. However, due to small sample sizes for students moving and changing schools these estimates were very imprecise. An alternative strategy to estimate the effect for local movers only is to only define the original moving-interactions that enter the regression (see page 7) for students not changing schools to start with. Using these interactions, I re-estimate all regressions of the main results table. Panel A in Table A2 shows the results. For example, the effect in column (4), where we control for neighborhood destination fixed effects, is estimated at 0.776 and not significant at conventional levels. This is very close to the main effect of 0.752 from the corresponding

[29] Table with all results available on request, omitted for space reasons.

specification in the full sample (Table 7).

Secondly, throughout we have kept ‘stayers’ in the regression to compute the various fixed effects (i.e. neighborhood and school fixed effects). These students were also included to gain precision but their inclusion should not drive any of the results. This is why I also estimate the main specification in a sample of ‘movers’ only. This modification of the control group brings down sample size from over one million to 190,588 students. As we can see in column (4) of panel B, in this sample the corresponding causal effect of moving before the test is estimated at 0.632 with a standard error of 0.513. Again, these estimates are very similar to the main findings and I conclude that my main results are insensitive these modifications.

7.4. Sample selection, imprecise measure of timing

I further checked the sensitivity of the main finding against specific sample selection issues. One concern is that the KS3 test is not taken on the exact date that residential information is collected. In particular, the residential information is collected mid of each January, while the KS3 is taken over the spring. This means that up to a third of students coded as moving in year nine to ten might in fact have moved just before the KS3 tests were taken, although residential mobility is usually lower during the winter period. I therefore re-run the main specification excluding from the analysis all students for whom I cannot be fully confident that they moved after the test was taken. This means that we now compare KS3 test results of students who move into social housing neighborhoods in the academic years seven to eight or eight to nine to students who move into social housing neighborhoods in the years ten to eleven only. The estimates for this sample, positive 0.601, compared to 0.752 in column (4) of Table 7, and statistically insignificant, remains in line with our main results.

7.5. Different time window and exposure times

Another potential concern is that it takes longer for neighborhood effects to operate. To at least partially address this concern, Table A4 includes students who move between the academic years six, which corresponds to the end of primary school, and year seven, the first year of secondary education. Hence, here we compare students who move into high-density social housing neighborhoods during the three (not two) years prior to taking the KS3 test to students who move during the first two years after the test. The cost of this setup is a reduction in sample size since we cannot follow all cohorts for this extended period. Two estimates are reported in the first row, where the first estimate is the effect of moving into social housing before the test, here between the academic years six and nine. The second row shows the coefficient for the dummy that indicates if a student moves into a social housing neighborhood at some point over the study period, here the extended period from academic year six to year eleven. Moving from columns (1) to (4), individual controls including KS2 test scores, school fixed effects and finally neighborhood fixed effects are included.

Just as before, the estimate for the effect of moving into social housing before the KS3 test is never sizeable nor statistically significant in any of the specifications. The unconditional estimate equals −0.990, but turns positive to 0.883 once control variables are included, remains positive (0.864) in column (3) and becomes close to zero (0.083) once neighborhood fixed effects are included. Again, none of these estimates is statistically significantly different from zero, and I conclude that moving into a social housing neighborhood during the three years prior to the KS3 test again does not correlate with the results.

8. Discussion and conclusions

In order to identify the causal short-term impact of neighborhood deprivation on student attainments this study exploits the timing of moving into these neighborhoods. Using this approach, there is no evidence for otherwise negative effects on age-14 test scores. The neighborhood level treatments are large and I also control for a direct effect of moving. This suggests that the existing and severe underachievement of students who move into high-density social housing neighborhoods cannot be causally linked to place characteristics during the early formative teenage years, although neighborhood effects on test scores might exist for different age groups or over the longer run.

The focus of this study is on short-term effects coming from exposure to new neighborhoods of up to three years only, and it is worth discussing this limitation a little further. Unfortunately, the research design that focuses on variation of the timing of the move, which turns out important to control for sorting, at the same time precludes any longer term analysis. It is thus not possible to draw similar conclusions regarding longer-term effects of living in highly deprived neighborhoods without making further assumptions. Similarly, the effect of growing up in social housing neighborhoods remains unidentified because we have to focus on movers to find variation in neighborhood quality over time. While the latter restriction presents a challenge for neighborhood-effects research in general, some speculations can be made about potential longer-term effects. In particular, since we can reject very small effects in the short run, large longer-run effects are only possible if there exist a strong non-linearity in the time it takes for neighborhood effects to operate. To date, I am not aware of any research that makes these claims but fully acknowledge this limitation of my approach. At least for short-run effects and for students moving into these neighborhoods, this approach allows us rejecting negative effects at unprecedented precision.

A further important limitation of this study is that I cannot exactly identify which students are moving into social housing on the individual level. Instead, I have to rely on tenancy information on the Output Area neighborhood level. In my baseline strategy I define students moving into a very small area that has at least eighty per-cent social housing tenants as “moving into social housing”. I have demonstrated that these are among the worst neighborhoods in England but my analysis cannot say anything about other deprived neighborhoods with lower shares of social housing, or about lower density social housing neighborhoods. I address this limitation in a number of robustness checks but ultimately cannot fully exclude that this measurement error affects my results. Future research could try to link individual tenancy information to student test scores directly.

Finally, it is worth discussing why families voluntarily move into the highly deprived neighborhoods to start with, and whether the finding of non-negative effects, once we identified a suitable control group, should be surprising in this context. Firstly, note that the finding of non-negative effects on teenage test scores should only be unsurprising in this setting in either of two cases: First, a family’s choice to move into a high-density social housing neighborhood could be at least partly motivated with regard to their children’s educational outcomes. Second, other factors that make social housing the preferred option in the choice set of the parents could be correlated with children’s education outcomes. Unfortunately, little data is available about individual motivations for moving into social housing in England. However, the former claim seems difficult to justify given that most students do not even change their schools when they move into social housing. Regarding the latter, qualitative evidence suggests that tenants primarily value the stability of social-housing tenancy. The fear of

Table A1
Data sources.

Dataset	Variables	Access
National Pupil Database –Annual school census (formerly PLASC)	From the 2001/02 cohorts onwards, detailed student-level information such as ethnic background, free school meals eligibility (FSME), and students' postcode of residence is collected. People eligible for FSME are likely to receive Income Benefits, Job-seekers' Allowance and to be single parents with a dependent child (Hobbs and Vignoles, 2007). This variable serves as proxy for the lowest income groups	Department for Education, England
National Pupil Database – Key Stage test scores	Test results for compulsory English, mathematics and science for age-11 (Key Stage 2) and age-14 (KS3) students. Teacher assessed scores for English and mathematics for age-7 students (KS1). Collected in May	Department for Education, England
Neighborhood variables	The 2001 Census of Population is the most recent available decennial survey of all people and households living in England and Wales. A wide range of socioeconomic variables was collected and made available at various levels of spatial aggregation	UK Dataservice
Social Housing Waiting List	Waiting list information on the Local Authority level for England	Department for Communities and Local Government
House price data	Information about final sale price for properties financed through the nationwide building society between 2000 and 2006	Proprietary dataset but other house price data is available for the UK

Table A2
Main results using different control groups.

	(1)	(2)	(3)	(4)
Panel A: Students not changing schools				
Move into SH neighborhood before KS3, between years 6 and 9	0.704	1.037	1.009	0.776
	(1.02)	(0.574)	(0.543)	(0.593)
Move into SH neighborhood before or after KS3, between years 6 and 11	−13.228	−3.022	−1.627	0.249
	(0.772)**	(0.126)**	(0.410)**	(0.463)
Panel B: Only movers				
Move into SH neighborhood before KS3, between years 6 and 9	−0.162	0.654	0.632	0.710
	(0.939)	(0.533)	(0.513)	(0.775)
Move into SH neighborhood before or after KS3, between years 6 and 11	−12.347**	−3.224**	−1.966**	−0.866
	(0.721)	(0.403)	(0.387)	(1.074)
Controls for effects of moving	Yes	Yes	Yes	Yes
Control variables (individual, school)	No	Yes	Yes	Yes
School fixed effects	No	No	Yes	No
Output Area fixed effects (after move)	No	No	No	Yes

Notes: Variable definitions as in Table 7. Panel A re-estimates the first four columns from Table 7 using only students who did not change school when moving, and Panel B using only students who moved, as control groups. The sample in Panel A has 1,063,435 students in 109,868 neighborhoods and 2442 schools. Panel B has 190,588 students in 79,718 neighborhoods and 2250 schools. Standard errors are in parenthesis and clustered at the neighborhood level.
** Sig. at 1%.

'Rachmanism', which is exploitation of tenants by unscrupulous landlords, is a factor raises the attractiveness of the social rental sector relative to the private sector (see Hills, 2007, p.18). Whether the potentially resulting increase in parental wellbeing filters down to teenage test score results is unclear. For example Kling et al. (2007) find positive effects on wellbeing of moving into a better neighborhood in the MTO experiment but nothing on school test scores. Future research could examine if the institutional differences that increase the attractiveness of stable social housing tenancy arrangements correlate with test scores for reasons independent of neighborhood quality.

Acknowledgments

Helpful comments from Sascha Becker, Thomas Breda, Christian Hilber, Ifty Hussain, Victor Lavy, Tim Leunig, Steve Machin, Alan Manning, Richard Murphy, Henry Overman, Frédéric Robert-Nicoud, Stephen Ross, Olmo Silva, Petra Todd, and Yves Zenou, and participants of the RES Annual Conference in London, the EALE/SOLE conference in London, the NARSC Urban Economics Association Conference in San Francisco (where an early version of this paper won the best graduate paper award), the Spatial Econometrics Conference in Barcelona, the LSE-SERC Urban Economics Seminar, the LSE-CEP Labour Market Workshop, the 2010 IZA Summer School, the 2010 ZEW Workshop on "Evaluation of Policies Fighting Social Exclusion"; and the CEP-CEE Education Workshop are gratefully acknowledged. I also acknowledge constructive criticisms of two anonymous referees and the editor. Previous working paper versions: Weinhardt (2010, 2013). ESRC funding gratefully acknowledged (Ref: ES/F022166/1, ES/J003867/1). I declare that I have no relevant or material financial interest that relate to the research described in this paper. All remaining errors are my own.

Appendix A

A.1. Housing Benefits

In England, parents on low incomes or who are unemployed can claim housing benefit, which essentially covers part or up to one-hundred per cent of their payable rent. The eligibility rules over the study period were set in 1988, which is prior to the period of this study (Hills, 2007, p. 115).[30] Importantly, housing benefits are awarded independently of tenure status and equally to parents living in the private rented or social housing sector or even in temporary private accommodation. The exact amount of housing benefit paid depends on a number of factors including the number of

[30] Recent changes to this policy following the last general election post-date the study period.

Table A3
Balancing regressions by type of move.

Dependent variable: KS2 test scores	(1) Moving into SH n'hood, OLS	(2) Non-SH n'hood move, OLS	(3) Moving into SH n'hood	(4) Non-SH n'hood move
Move before KS3	−0.112	0.671	0.070	0.622
	(0.979)	(0.132)**	(0.961)	(0.124)**
Move	−13.511	−4.414	−7.901	−3.165
	(0.757)**	(0.105)**	(0.744)**	(0.098)**
School FX	NO	NO	YES	YES

Notes: 1,063,435 student observations. Columns (3) and (4) include 2442 school fixed effects (for descriptive statistics see column 4 of Table 1). Errors clustered at neighborhood level. Standard errors in brackets.
** Sig. at 1%.

Table A4
Expanding the treatment period, years 6–9 and years 9–11 movers.

	(1)	(2)	(3)	(4)
Move into SH neighborhood before KS3, between years 6 and 9	−0.990	0.883	0.864	0.083
	(1.348)	(0.825)	(0.783)	(0.992)
Move into SH neighborhood before or after KS3, between years 6 and 11	−12.767	−3.596	−2.344	−0.177
	(1.145)**	(0.704)**	(0.669)**	(0.861)
Control for moving into social housing	Yes	Yes	Yes	Yes
Controls for effects of moving	Yes	Yes	Yes	Yes
Ethnicity-controls	No	Yes	Yes	No
School fixed effects	No	No	Yes	No
Output Area fixed effects (after move)	No	No	No	Yes

Notes: Here we compare KS3 scores for pupils who move into social housing neighborhoods during three years prior to taking the KS3 compared to pupils who move during the two years afterward. All other definitions and restrictions remain the same. The estimates are based on one cohort with 280 k student observations and 2419 schools.
** Sig. at 1%.

children, income and savings but also on the 'local reference rent', which is determined by local housing officials and effectively sets a maximum for what constitutes a 'reasonable' rent in the private sector. Depending on these circumstances housing benefits can cover the full rent. For central London, for example, the corresponding rent for a 2-room flat (i.e. one bedroom, one living room) was 290 lb per week in December 2005 (Hills, 2007, p.116). Importantly, housing benefits are responsive to residential changes or changes in rent; hence families who get offered a place and move into social housing where rents are fifty to sixty per cent lower than in the private rented sector will face an immediate and simultaneous reduction in housing benefits.

This responsiveness to residential changes or changes in rent in important for this study. It means that families who get offered a place and move into social housing where rents are fifty to sixty per cent lower than in the private rented sector will face an immediate and simultaneous reduction in housing benefits. This institutional setting gives rise to a unique situation where we do not expect any direct income effects from moving into social housing.

Note that I generally include free school meal status, a time-varying control for parental income, as a control variable in Eq. (7). The inclusion of this additional control variable makes no difference to the interpretation of the results. Further, Section 7 shows that early and late movers are identical even with respect to their time-varying free school meal eligibility. Therefore it is unlikely that any income effects confound interpretation of the results.

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