# Moving Opportunities: The Impact of Public Housing Regenerations on Student Achievement

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# Moving Opportunities: The Impact of Public Housing Regenerations on Student Achievement*

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**Abstract**

Neighborhoods can considerably affect children's future outcomes, but the forces through which they operate are not well understood yet. I study how local schools affect the educational achievement of low-income students when their neighborhood changes as a result of an inflow of more affluent households. I use public housing regenerations in London as a natural experiment which caused little displacement of local families and changed the composition of more deprived neighborhoods. I built a novel database by geocoding all regenerations and linking them to administrative records on primary school-age students. I compare the achievement of students in schools of the same neighborhood but located at different distances from the regeneration before and after its completion, and estimate the impact on students who were originally enrolled in local schools before completion. Such students have higher test scores at the end of primary school after the regeneration. Gains are stronger for more disadvantaged and low-ability students. The empirical evidence suggests that such gains are driven by changes in the demand for schools due to the inflow of more affluent parents with strong preferences for school quality.

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# 1 Introduction

Neighborhoods play a substantial role in shaping child development and later adult outcomes, and children living in high-poverty areas are the most affected. Moving from a high-poverty to a lower-poverty neighborhood improves a number of children's future outcomes, such as high school dropout rates, college attendance, earnings, employment and intergenerational mobility (Chetty et al, 2016; Chetty and Hendren, 2018; Chyn, 2018; Laliberté, 2018). Importantly, the timing of relocation turns out to be crucial, as neighborhoods seem to affect later life outcomes mainly through childhood exposure.

The specific driving forces of these effects are still unclear. A sizeable literature shows that educational inputs during childhood, and school quality in particular, have long-lasting impact on future outcomes (see, e.g., Heckman, 2006; Deming, 2009; Chetty et al., 2011). However, empirical evidence on the role of this channel in explaining differences in later outcomes when children move to a different neighborhood is scarce. Indeed, when children's neighborhoods change it is hard to narrow down what drives their long-term outcomes as multiple inputs change at the same time, such as neighborhood amenities, crime rate and the quality of school attended.

I study how local schools affect the educational achievement of low-income students when their neighborhood changes as a result of an inflow of more affluent households. Specifically, I use regeneration programs of high-poverty public housing estates in the UK as a natural experiment changing the composition of more deprived neighborhoods. In London, between 2006 and 2016 about 230 public housing buildings have been demolished to pave the way for new high-density buildings. The buildings slated for demolition, originally hosting about $77,600$ individuals, became home to approximately $159,600$ over the period considered. I have collated information on these regeneration programs in a novel database using planning applications records from the London Development Database (LDD). Each program is geocoded within a census block - narrowly defined areas spanning about 0.25 square miles - and linked through the latter to administrative records covering 15 cohorts of primary school-age children living on the regeneration site and the surrounding neighborhood.[1]

A distinctive feature of UK public housing regenerations with respect to other programs (such as the US HOPE VI program) is that they drive little displacement of local families

[1]My analysis considers state-funded schools, which enroll over 95% of primary school-age children as the market for private schools is very small at this education stage.

and their children. They do target public housing in more deprived neighborhoods but they are seen as an opportunity to revitalise local communities rather than to move their residents away (Mayor of London, February 2018). Families are typically relocated in the surrounding neighborhood and their children keep attending local schools. Life-time social renters have a further right to be offered a house in the new premises and have therefore the opportunity to move back.

I start my investigation documenting that the new developments attract a substantial amount of more affluent households. The new constructions contain a sizeable number of new living spaces, 50% of which - on average - will be sold on the private market. The new housing units would typically appeal to more affluent households, as can be seen from Figure 1. This drives a substantial inflow of new households and children, leading to an average increase of 14 kids (about 12%) living on the regeneration's block and a change in student composition, as 84% of incoming children are not eligible for subsidized lunches; 60% of them are first and second graders, accounting for about $6-8\%$ of a school grade enrolment. House prices around the regeneration program's site increase by $1.2-1.7\%$ after the reconstruction, showing that the programs spur neighborhood gentrification as the surrounding area also gets targeted by more affluent households.[2]

In this setting, the ideal experiment would compare student outcomes in otherwise identical schools except for the development of a regeneration program in the nearby neighborhood. I take this idea to the data by comparing students attending schools enrolling mostly children living on the regeneration site (treatment), to those attending schools located in the same neighborhood but farther away from a regeneration and therefore enrolling students from a different catchment (control). To take stock of my research design, I use the regulation of primary school admission and exploit the fact that London schools tend to be oversubscribed and school offers depend on school-home distance. I further exploit availability of detailed data on children's block of residence to control for fixed unobserved attributes at this level.

As schools in London are typically small – with one or two classes per grade – and operate at full capacity, it is hard for families to move their children across schools because they face substantial financial and non-financial costs. For instance, when families relocate to a new neighborhood they don't have full control over the choice of a new school as many schools work at full capacity. I use a grandfathering instrument to adjust for mobility and estimate

[2] These figures are not distant from those obtained by Koster and Ommeren (2018), who show that public housing renovations in the Netherlands increase surrounding house prices by about 3.5%.

the impact of the programs on students who were originally enrolled in local schools before the regeneration. I exploit the fact that students who were enrolled in a school close to a regeneration program before its expected date of completion are guaranteed a school place, so that in practice their enrollment into such schools after the regeneration can be considered passive (see, e.g., Abdulkadiroglu et al., 2016). The underlying assumption is that enrolment decisions were not driven by expectations about the regeneration programs. Firstly, there is no certainty about the exact date of start and completion of each program. Secondly, there is uncertainty on which schools can be targeted by parents after the end of the regeneration, as school catchments vary over time and depend on the degree of oversubscription and each year's specific pool of applicants. This strategy identifies the causal effect of regenerations on scores of students who took the test in treated schools because they were originally enrolled there before the regeneration.

I show that children who were enrolled in schools closer to the program's site before its completion have higher math and language test scores at the end of primary school (when they are aged 11) with respect to the control group. At the end of primary school, when they are aged 11, students sit national standardised exams in math and English language. I find that, on average, achievement increases by $0.06\sigma$ and $0.08\sigma$ (1.3 and 0.75 points, or about $1.9-2.5\%$ of the average) in math and language respectively. Results are stronger for children belonging to more disadvantaged households and for children with low or average baseline achievement (measured at age 7). Placebo estimates obtained by imputing the regeneration's completion before the actual date are fairly precise zeros.

I then use the research design to investigate the role of local schools to explain this change. I start by showing that class-level peer effects within school are unlikely to be at play. On one hand, the little displacement generated by the programs implies little changes in last school grades; on the other hand, affluent families relocating to the new building and whose older children are in later school grades tend to leave the latter in their original school. The latter fact is consistent with the idea that parents do no have perfect control on the school choice if they move after the first year of school, and they may therefore prefer to keep their kids in the old school when they move and be on a wait list for the new school.

However, I show that affluent families relocating to the new premises with children at younger ages (the school starting age is $4-5$ years) do start populating local schools from the first year. Since school admission runs by distance to home, compared to families with older children already enrolled elsewhere, the former don't have the option of sending their child to a school located in a different neighborhood. While it is not possible to completely exclude within school cross-grade peer effects, an alternative explanation in this context is that new parents exert pressure on local principals to improve their schools, generating spillovers to other grades. Indeed, one reason why student achievement is particularly low in more deprived areas is that their residents have specific preferences over school quality and distance. Hastings et al. (2010) show that disadvantaged families exhibit preferences for school distance over school quality, whereas more affluent households exhibit strong preferences for school quality. As a result, schools in more deprived neighborhoods can act as 'local monopolists' and have therefore very little incentives to improve. Importantly, this does not necessarily need to be 'initiated' by the parents, as principals may have the incentive to raise school performance in order to attract the newcomers and increase the school roll and its 'quality'.

Finally, I look at 'direct' neighborhood peer effects that could be driven by the regeneration. For instance, the program itself might include new amentities (e.g. parks, playgrounds) where children can interact. If this were the case, one would expect the achievement gains to be greater for children living on the regeneration site or very close. I therefore re-estimate my model for students living at different distances from the regeneration site but attending the same school, and show that educational gains are not larger for students living closer. Regenerations themselves may also reduce crime in the neighborhood as shown by Aliprantis and Hartley (2015) and Sandler (2017), thereby generating a better environment for locals. However, I show that crime rates do not change after the regeneration, consistently with the intuition that such regenerations are carried out in more deprived, but not extreme-poverty, neighborhoods.

Why should the fact that schools are the main driver of neighborhood effects be of interest to researchers and policy-makers? In this setting, the inflow of affluent households in more deprived neighborhoods changes - in the short-run - only the share of affluent kids attending local schools, leaving other margins (such as neighborhood amenities and crime) unaffected. This experiment suggests therefore that neighborhood effects in the literature are likely mediated by the different school quality experienced across different neighborhoods. This result is similar to recent findings by Laliberte (2018), who argues that between 50% and 70% of neighborhood effects are due to differential access to (good) schools. However, the latter paper still relies on a movers design, whereas I can compare over time 15 cohorts of students in schools located in the same neighborhood, but differentially exposed to more affluent households.

This paper also contributes to a broader - policy-relevant - issue represented by the lack of mobility of low-income families. Bergman et al. (2019) show that part of the reason why low-income families don't move to better neighborhoods is because they face a number of financial and non-financial barriers in the housing search process. My results show that it is possible to create opportunities directly in more disadvantaged neighborhoods and improve the (educational) outcomes of children living there, rather than moving them away.

Finally, I contribute to the literature studying the effects of public housing interventions. The latter has focused on short- and long-term outcomes of the households displaced by the demolition (Jacob, 2004; Chyn, 2018), but no evidence exists on the consequences of such programs on those who stay in the targeted neighborhood. My analysis shows that public housing regenerations have the potential to also play a substantial role in raising student achievement during childhood in such neighborhoods, and thereby their future outcomes (Heckman, 2006; Chetty et al, 2016; Chetty and Hendren, 2018).

This paper is organised as follows. Section 2 describes the history and regulation of public housing regeneration projects in London and provides an overview of the UK primary school system, as well as of the works studying the consequences of public housing policies. Section 3 describes the different data sources employed and the sample construction. Section 4 describes how regeneration programs affect the targeted building and the local neighborhood. Section 5 shows how regenerations affect student performance in local schools. Section 6 shows how regenerations affect the achievement of students who were already enrolled in treated schools before the regeneration's completion. Section 7 summarises the main robustness checks. Section 8 evaluates different potential mechanisms that may explain the results. Finally, Section 9 concludes with some final remarks.

# 2 Institutional Background and Context

## Public Housing in London

Most public housing estates in London (akin to the US 'projects') were built between 1950 and 1980. The property and management of such estates rests on the 33 Local Authorities (LAs) into which London is divided. LAs – or 'local councils' – represent the local government units in England and are responsible for a range of services, such as education and housing.[3] In 1985 and 1988, two housing acts facilitated the possibility for LAs to transfer the management of their public housing stock to housing associations. The latter are non-profit organizations, and in 2003 they were managing approximately one-third of the total public housing stock (about 5.2 million housing units).

Any adult individual who has low income (as defined by every single LA), has recognized housing needs, has lived for a certain number of years in the LA, and hasn't displayed situations of anti-social behavior or rent arrears, can apply for public housing. Once an individual meets these eligibility criteria he or she joins a waiting list and can apply for housing as properties become available. Priority is given to people with medical or welfare needs, those living in unsatisfactory conditions (e.g., overcrowding), and the homeless. Individuals can become tenants for a fixed number of years (flexible tenancy) or for their entire life (secure tenancy). Secure tenants can also become eligible to buy their house through the so-called Right To Buy scheme and therefore become homeowners.[4] In 2001, there were about $790,000$ public housing units in London, providing affordable housing for about 26% of the 3 million households in the city. Of the $790,000$ public housing units about $530,000$ were still managed by the London LAs, whereas the rest were managed by housing associations.

Table 1 shows a number of descriptive characteristics for individuals (Panel A) and children (Panel B) living in London in private and public housing, using both the 2001 census and the National Pupil Database. Individuals living in public housing tend to come from minorities as they have a lower probability of being white. They also have a higher probability of having a low-skilled job and of being unemployed, and a lower probability of owning a car. Their children have a higher probability of being eligible for subsidized school lunches or for SEN support, and have higher deprivation scores.[5]

[3]In some parts of England there is a further subdivision whereby some services (e.g., housing, waste collection) are devolved to lower layer units know as non-metropolitan districts. Since this is never the case for London, this distinction is irrelevant in this context.

[4]The *Right-to-buy* scheme helps public housing tenants to buy their home by benefiting from a consistent discount. House and flat tenants can benefit from a 35% and 50% discount, respectively after they have been public sector tenants for three years. After 5 years the discount increases by 1% and 2%, respectively, up to a maximum of 70%.

[5]Characteristics of children living in public housing are proxied using children living in the census blocks targeted by a regeneration program. However, their figures (Table 1, Panel B) are broadly consistent with those for the households obtained from the 2001 census.

## Public Housing Regenerations

As the property of public estates ultimately rests on the LAs, regeneration decisions are also taken by the latter. Local councils should prioritize buildings for regeneration based on their estimated level of unfitness (poor design and poor condition). However, it is often the case that regeneration programs including the demolition of existing premises and the subsequent construction of new buildings facilitates the sale of a substantial number of the newly built housing units on the private market.[6] This implies that in practice councils may have the incentive to prioritize buildings – or even entire estates – located in more 'profitable' neighborhoods.[7]

During the demolition, tenants are moved to alternative public or private accommodation, located either in the preferred area or one that minimizes disruption to the household's work and schooling circumstances.[8] Secure tenants have the right to be offered a flat in the new premises, while house owners are offered a price for the flat. After permission is granted for the demolition, it takes on average 11 months to start the demolition and 24 months to complete. These regenerations are also considered an opportunity to increase the housing stock, and therefore they often entail a sizeable increase in the number of houses provided on site. Among all regenerations collected, the demolished buildings contained about 70 housing units on average, whereas the new buildings contained 160 units. This implies a larger housing density, with a net increase of about 90 housing units on average per regeneration.

Figure 1 provides an example of a regeneration program carried out in West London. The new constructions offer better flats that can be very appealing for middle class households. Indeed, on average the price of houses transacted on the regeneration site increases by 25% compared to transactions carried out before the demolition. However, since some of the new houses still have to be reserved as public housing units, the share of units sold at the private market price varies depending on the program. In the entire sample of regenerations, on average 70% of units are deemed for public housing; considering larger projects only – the main object of this study – this figure drops to 50%. In some instances, very large regeneration programs can also include the provision of other new amenities for the local area, such as new parks or

[6]Regenerations are often carried out with the involvement of private developers through two approaches: the inclusionary and the linkage. Under the first approach, developers of market-rate housing are required to include as part of a new development a (minimum) percentage of units at below-market prices; under the second approach, private developers are either required to make cash payments into a housing trust fund (which in turn finances below-market housing developments) or to develop below-market housing at other sites.

[7]See, for example, https://www.theguardian.com/society/2017/oct/29/gentrification-pushing-out-the-poor-haringey-council-housing-battle-corbyn-labour.

[8]Households who have to move also get priority when bidding for vacancies advertised by the council.

playgrounds.

## Primary School Provision in England

In England, children enter primary school when they are aged 5 (grade 1). The first phase of primary school is Key Stage 1 (KS1) and lasts three years, at the end of which children are assessed in math, language and science by their own teachers. During this stage, teachers assign every student the 'level' they are working at in each of the three subjects. They can therefore be graded as working below the expected level (Level 2), at the expected level (Level 3), or above the average (Level 4). The second phase of primary school is Key Stage 2 (KS2), when students are aged 8 to 11. At the end of this stage all students take national standardized tests in math and language. These tests are proctored locally in every school and marked externally. Depending on the score attained in the standardized test, students are again assessed as working below, at, or above the average (Level 3, 4, and 5, respectively). Every year school performance averages are used to form school rankings that are made available to parents through the School Performance Tables.

The vast majority (about 95%) of primary school-age children are enrolled in public tuition-free schools. School entry is regulated by the LA, with parents able to rank up to 6 schools based on their preferences; in case of oversubscription, priority goes to children with SEN or with siblings at the school. However, other than this applications are mostly ranked by distance from the child's home to school.[9] Primary schools in England are very small (the average grade size in my sample is about 51), and the average catchment area in London is about 1km. Catchment areas are not fixed and depend on the number of places and specific pool of applicants in every year. Although parents can apply to schools outside their LA of residence, in practice this almost never happens and about 96% of primary school children attend a school in the same LA of residence.

Although most public schools are run by the LAs, since 2000 the so-called 'academies' have appeared. The original aim was to improve poor performing schools' results by giving headteachers direct control over their schools (Sponsor Led academies). However, in 2010 the program was expanded, and now every school can voluntarily decide to become an academy (Converter academies). As of July 2019, approximately $5,600$ primary schools, accounting for

[9] In some schools, such as faith of 'foundation' schools, the local governing body has direct responsibility for student admissions and may prioritize students according to different criteria, such as faith. However, selection based on ability is ruled out by law.

about 34% of all primaries, have obtained academy status. Almost all academies are represented by schools that have decided to convert and gain academy status rather than being new schools opening from scratch.

Like US charter schools, academies are public and tuition-free schools funded by the government but autonomous in a number of aspects such as staffing, provision of services (e.g., Human Resources), curriculum, and the educational approach (e.g., school philosophy).[10] Although they are free to set their own admission criteria, they must abide by the guidelines stated in the Admission Code and cannot select students on ability. In practice, this implies that most schools do not change their admission criteria after becoming academies.

## Related Literature

Exposure to more deprived neighborhoods can have long lasting impact on children outcomes. Chetty et al (2016) focus on the Moving to Opportunity (MTO) experiment, which offered randomly selected families living in public housing vouchers to relocate to lower-poverty neighborhoods. They show that relocating to a better neighborhood improves college attendace rates and earnings for children who were below age 13 at the time of the move. Chetty and Hendren (2018) further show that moving to a better neighborhood improves intergenerational mobility, and this happens through childhood exposure. Laliberté (2018) shows that moving to a better neighborhood improves a number of educational outcomes, such as university enrolment and years of schooling. However, even though poorer families can potentially benefit from moving to better neighborhoods, they might be constrained in their choice or have strong preferences over low-income neighborhoods. Bergman et al. (2019) focus on low-income families' residence choices, showing that families are willing to move to high-opportunity areas once they are provided with housing search assistance.

A number of studies have focused specifically on the outcomes of those living in public housing. Oreopoulos (2003) shows that children living in public housing across different neighborhoods and therefore exposed to different living conditions do not perform differently in the labor market. Van Dijk (2019) shows that on average moving into public housing negatively affects labor market outcomes, although this masks substantial heterogeneity depending on the

[10] Despite many similarities, there still are some notable difference between UK academies and US charter schools. The latter are often located in deprived areas and serve a large fraction of low performing or minority students, while English academies include a substantial number of high achieving schools. Additionally, whereas almost all UK academies are represented by school takeovers, in the US many charters are instead newly opened schools. Finally, while academies can only be nonprofit organizations, US charter schools can be run for profit.

neighborhood where the public housing is located. Other housing assistance programs have found to have very limited or even negative effects on labor market and educational outcomes (Jacob and Ludwig, 2012; Jacob et al., 2015).

Other works have dealt with public housing programs, focusing in particular on the demolition stage and its effects on the households which were displaced as a result of the demolition. Jacob (2004) studies the short-term effects of public housing demolitions in Chicago on the achievement of children who were displaced, finding no effects - likely because children ended up in schools very similar to the ones they left. Chyn (2018) studies the long-term impact of public housing kids' relocation to less deprived neighborhoods after demolition, and finds instead that relocated kids have better labor market prospects and lower high school dropout rates.

Other studies have focused on the impact of public housing programs on local house prices and crime. Koster and Ommeren (2018) finds that public housing renovations in the Netherlands increase surrounding house prices by about 3.5%. Aliprantis and Hartley (2015) and Sandler (2017) find that public housing demolitions in Chicago led to a sizeable decrease in violent crime rates in the surrounding neighborhood.

In addition to demolitions, public housing developments and urban regenerations programs can substantially affect the surrounding neighborhoods. Rossi-Hansberg et al. (2010) show that in neighborhoods targeted with urban residential revitalisation programs, land prices increased by $2-5\%$ per year after the program. Diamond and McQuade (2019) document how affordable housing developments lowered crime rates, attracted a racially and income diverse population, and increased house prices nearby in disadvantaged neighborhoods across 15 US states.

# 3 Data and Sample Selection

I consider 'large' regeneration programs involving public housing buildings in Greater London carried out between 2004 and 2013. Since the public housing stock is managed at local level by the LAs, a unified database including public housing buildings and their developments does not exist. I have therefore constructed a novel database with regeneration programs involving public housing buildings, and this has been linked to several other datasets. An overview of the different sources used and the sample selection is provided below.

## Administrative Sources

**Public housing regenerations.** I have constructed a database including all public housing regenerations in Greater London between 2006 and 2016 using administrative records from the LDD. The LDD contains all planning applications filed to the London planning authorities – represented by the 33 London local councils – *completed* after 2006 (as of November 2017 it contained 60,845 records).[11] I first tracked all applications including the regeneration of residential buildings (726 records as of November 2018) and involving public housing buildings. Since a database listing the stock of public housing does not exist, a building has been defined as being public housing if the new premises include at least 1 public housing units. I keep all planning applications which included a development, redevelopment or demolition of existing premises and whose planning application was initiated. With this procedure I collated an initial dataset with 469 residential demolitions, with the earliest initiated in 1999. Finally, all regenerations are geolocated and have been linked to their census blocks, small-level geographies with a target population of about 800 households and an average size of just above 0.25 square miles.[12]

**Student-level data.** This study employs administrative records from the National Pupil Database (NPD) on primary school-age students in England from 2002 to 2016 (approximately 600k per year). Data include student test scores in math and language at the end of the primary school cycle (KS2 scores) and each student's teacher assessments at the end of grade 3 (KS1). [13] The dataset also includes detailed student demographics, such as gender, ethnicity, language spoken at home, eligibility for subsidized lunches and SEN support, and every student's block of residence. Children are linked to regeneration programs through their block of residence.

**School-level data.** Data on school characteristics have been gathered from different sources. The NPD (2002 – 2016) contains information on school type and address, which is used to link schools to regenerations. The School Census (2006 – 2010) and School Workforce dataset

[11] The LDD is publicly available and updated monthly; the latest version can be accessed at: https://data.london.gov.uk/dataset/planning-permissions-on-the-london-development-database–ldd-.

[12] The census blocks considered in the analysis are the so-called Lower Layer Super Output Areas (LSOAs), a geographical layer developed by the Office for National Statistics (ONS) for census statistics reporting purposes. There are 4,765 LSOAs in London and 32,482 in England, designed to fit the boundaries of the LAs.

[13] Students are awarded a mark between 0 – 100 for math (0 – 110 from 2016 onwards) and 0 – 50 for language. Until 2012 the language exam carried 100 points, evenly split between a reading and a writing part. Since 2012 only the reading part has been maintained as part of the national standardized assessments, and therefore only this latter mark has been included as the language outcome. Moreover, the reporting of KS2 levels changed in 2016 and students were no longer awarded levels 3, 4, and 5 according to the test score achieved. I have retrieved the level that would have been awarded to every student for 2016 by inferring the level thresholds that correspond to the average test score distribution observed between 2002 and 2016.

(SWF, 2011 – 2016) contain information on teacher qualifications, teacher status (e.g., teaching assistants), the pupil-to-teacher ratio, and teacher absences. Finally, the Consistent Financial Reporting (CFR, 2006 – 2016) contains data on school funding broken down by funding category (e.g., learning resources, SEN funding, staff funding).

**House prices.** I use administrative records from the UK Land Registry on house transactions from 2002 and 2016. Every transaction records the date, price paid for the house, house type (detached, semi-detached, terraced, flat), house age (newly built or old), and contract type (leasehold or freehold).

**Census and crime data.** I exploit census data at block-level from the 2001 UK census. Block-level statistics include detailed information on population characteristics, such as ethnic composition, jobs, employment, education, and social status (e.g., car ownership, socio-economic class). Furthermore, I use crime data at block-level from 2008 to 2016 publicly available from the London Metropolitan Police website. The latter dataset records the number crime offences broken down by category (e.g. burglary, theft, violence against the person).

## Sample Selection

I exclude small public housing regenerations providing for less than 10 housing units in the new building, which leaves 227 regenerations in the sample. Then, I exclude those whose permission date was granted before 2004 (to allow for at least 2 years of pre-treatment periods) or after 2013 (to allow for at least 1 year of post-treatment periods). Among the remaining regenerations (145), only those involving 'large' buildings, defined as those with at least 75 housing units (similar to the definition of high-rise buildings in Jacob, 2004), have been kept. For the main analysis, every demolition is linked to nearby schools up to 2km away and to all children attending such schools.[14] Finally, only regenerations for which it was possible to find at least one treated and one control school have been retained. This leaves me with 39 demolitions, 405 schools (261 treated and 144 control) and $179,835$ children ($102,924$ and $76,911$ control).

I consider two alternative samples. The average primary school catchment area in London is 0.95km, and I therefore first consider all children attending a school located within this

[14]There are two cases of 'ties' in which one block experiences more than one regeneration or one treated school is assigned to multiple regenerations. In the first case I have kept only the first regeneration occurring in the block, deleting the next ones from the sample. In the second case, I assign the treated school to the regeneration occurring first among the ones the school has been assigned to in the first place.

distance from a regeneration as 'treated'. Roughly 70% of children attend a school located within this distance from their residence. Given that the average student-school distance is about 1km, a potential control group could be represented by all students attending a school located between 1 and 2km from a regeneration. However, one may worry about possible spillovers, not least because schools in more deprived areas are less likely to be at full capacity and therefore catchment areas might be larger than the average. As 80% of students attend a school located within 1.3km of their residence, I consider a 'buffer' zone of about 300 meters and consider an alternative 'treated' sample that includes all students attending a school located within 1.3km of a regeneration. I then define as 'control' children all those attending a school located between 1.3 and 2km from the regeneration. I use the first treatment group (all schools within 0.95km) to define a 'narrow' sample, and the second treatment group (all schools within 1.3km) to define a 'loose' sample. Figure 2 shows an example of the logic used to construct the two samples, while Table 2 provides several summary statistics for the two samples employed.

Public housing buildings are spread around the urban area and are present in almost all local councils, as shown in Figure 3. Red dots represent 'large' regenerations included in the final sample, demonstrating that the selected sample is geographically representative of the 'population' of regenerations. Panel B shows how regenerations are distributed in Southwark, one of London's local councils, and provides an example of the block (LSOA) geography (black outline). Since student-level data are available only from 2002 to 2016, it is not possible to observe every regeneration for the entire time span considered (13 years, 6 before and 6 after the permission date). This can be seen from Figure 4, which shows the distribution of regenerations over time.

Table 1 displays summary statistics for the population and children living in blocks with a regeneration (column (5)) and with a 'large' regeneration (column (6)), showing that – consistent with the statistics concerning the broader population living in public housing (columns (2) and (3)) – households and children living in the blocks affected tend to be substantially more deprived than the London average along many dimensions. The juxtaposition of columns (5) and (6) also indicates that the final sample of regenerations does not seem to be selected along any crucial dimensions (except for a larger fraction of white and a lower fraction of Asian children) with respect to the sample also including smaller regenerations.

# 4 The Impact of Regeneration Programs on Local Residents

The empirical investigation begins by studying how regeneration programs affect the households living on the program site. Since these programs include the demolition of existing premises and the construction of new buildings, they may potentially generate a substantial outflow and inflow of households and children. Figure 5 shows the percentage of children moving out in the blocks targeted by a regeneration project; Panel A shows the trends for regeneration projects involving smaller buildings, whereas Panel B considers larger buildings.[15] As indicated by Panel A, regeneration projects involving smaller buildings generated little displacement of children. Panel B shows instead that regeneration projects involving bigger buildings do generate an increase in the percentage of children moving out (solid line), with the peak occurring exactly on the permission year. However, this panel also shows that the vast majority of children who had to move out did so by relocating within 1km of the regeneration (dashed line). In the short-term, this is what one would expect given the regulatory provisions outlined in Section 2.

I then characterize the new residents considering the following equation using outcomes at block level:

$$Y_{byt} = \pi_0 + \pi_1 D_{0b} \cdot T_t + \eta_b + \psi_y + \delta_t + \kappa_{byt} \tag{1}$$

where $Y_{byt}$ is the outcome for block $b$ in year $y$ and time $t$. $D_{0b}$ is the treatment dummy, taking a value of one for all blocks facing a regeneration program and zero for all blocks between 1.3 and 2km from the regeneration. $T_t$ is the time indicator and takes a value of one after the expected end of the regeneration. $\eta_b$, $\psi_y$, $\delta_t$ are block, year and time fixed effects, respectively. Figure 6 presents the results from a version of equation (1), where I add leads and lags interacted with the treatment indicator to explore the outcomes' trend over time. Results are shown for the number of children (Panel A) and the number of children not eligible for subsidized lunches (Panel B).

Following the completion of the program, set between 2 to 3 years after the permission date, the number of children living in the block (Panel A) increases over the next two years (and

[15]The stratification considers as 'small' and 'big' regeneration projects that provide for a number of housing units below and above the average (117 units) among all regenerations involving the construction of at least 10 units. The construction of big buildings is highly correlated (0.76) with the presence of a large building already on site that was demolished.

remains flat afterwards) by approximately 13 children (representing an increase of about 4% compared to the average school roll). This increase in the number of children is almost entirely driven by the increase in the number of students who are not eligible for subsidized lunches (Panel B). This figure also shows that, besides an increase in the number of children, the new premises are targeted mostly by more affluent households.

Finally, I consider changes in house prices on the regeneration site and around. House prices on the regeneration site increase by 25% with respect to the transactions carried out before the regeneration, showing that the new housing units are indeed newer and better than the existing ones.[16] Additionally, this study explores how regenerations affect the surrounding area in terms of house prices in the short-term. Therefore, I consider the following difference-in-differences (DID) equation:

$$Y_{hpmyt} = \theta_0 + \theta_1 D_{hp} \cdot T_t + \theta_2 W_{hpmyt} + \rho_p + \tau_m + \psi_y + \delta_t + \mu_{hpmyt} \qquad (2)$$

where $Y_{hpmyt}$ is log (deflated) price paid for transaction of the house $h$ located in postcode $p$; $m$, $y$ and $t$ indicate month, year, and time, respectively. $D_{hp}$ is the treatment dummy and – following the logic outlined in Section 3 – takes a value of one for all houses transacted up to 1.3km from the regeneration, while $T_t$ is again the time indicator for all transactions completed after the expected end of the regeneration. The control group includes all transactions conducted between 1.3 and 2km from the regeneration. $W_{hpmyt}$ is a vector of house characteristics (house type, age, and contract type); $\rho_p$, $\tau_m$, $\psi_y$, and $\delta_t$ are postcode, month, year and time fixed effects. Standard errors are clustered at postcode level.

Table 3 shows the results for house prices considering transactions within 0.95km (columns (1) to (3)) and 1.3km (columns (4) to (6)) of the regeneration site. The most complete specifications (columns (3) and (6)) imply an average increase of $1.2-1.7\%$. House prices are increasing over time, resulting in a figure which is $1.9-2.3\%$ higher four years after the end of the program. Estimates for the loose sample have a lower magnitude, consistent with the intuition that housing externalities stemming from the new building will be larger for houses

[16]This figure represents the unconditional price change and compares houses transacted one year before the permission year with houses transacted one year after the expected end of the program. As I only have the geographic coordinates rather than the building's postcode, I consider all transactions involving the new housing units as those referring to houses within 400 meters of the regeneration, representing the average length of the new site's area (1.6 hectares).

located closer. Higher house prices in the surrounding neighborhood suggests that the latter will also eventually be targeted by more affluent households that can afford more expensive houses. This implies that such programs have the potential to lead to a substantial gentrification of deprived neighborhoods in the medium-term.

# 5 Regenerations and the Achievement of *Local* Students

In this Section, I focus on the impact of housing regenerations on the achievement of students attending the schools nearby. Here, the main empirical challenge arises from the choice and timing of regeneration programs. As more than 50% of the housing units created in the new buildings are sold on the private market, local councils have an incentive to prioritize those buildings that can maximize the revenues . Indeed, although councils should prioritize estates based on conditions of unfitness – poor design and poor condition – in practice they have often been accused of social cleansing and of targeting buildings or estates located in more profitable areas.[17]

I overcome this challenge by exploiting variation in children's educational outcomes within schools located in the same school district, but at different distances from the regeneration program site, before and after its completion. Specifically, the study employs a DID strategy that compares students enrolled in schools close to a regeneration – local or 'treated' students – with students enrolled in schools located farther away from the regeneration – 'control' students. The underlying logic of this idea is that regenerations will potentially affect all students enrolled in schools representing a possible target for the children of the families living on the regeneration site. Since students from different neighborhoods may sort into the same school, I also control for fixed unobserved attributes of a child's block of residence.

Table 4 shows summary statistics for the treatment groups (columns (1) to (4)) and the control group (columns (5) and (6)). The two groups of students and schools are remarkably similar in terms of observables. A sizeable difference can be observed only for students' SES , with treated students that happen to have a larger probability of being eligible for subsidized lunches. Smaller differences can be observed for student achievement (slightly lower in the treatment group at both KS1 and KS2) and for ethnic composition, with a slightly lower (larger)

[17]Public housing regeneration projects have received extensive media coverage by the main British newspapers, such as The Guardian. See for instance: https://www.theguardian.com/lifeandstyle/2018/nov/21/urban-regeneration-scheme-mask-problems-communities; https://www.theguardian.com/society/2017/jul/21/the-real-cost-of-regeneration-social-housing-private-developers-pfi.

proportion of white (black) among the treated children.

Importantly, as shown in Figure 7, both groups follow similar parallel trends in the outcomes up to the treatment event. The treatment event is set between 2 and 3 years after the demolition (when the new building is expected to be completed), and the Figure shows pre-trends in math (Panel A) and language (Panel B) students' test scores at the end of the primary school cycle. This is the key identifying assumption required by the DID in this framework – that KS2 test score trends would be the same in treatment and control schools in the absence of the regeneration. Treated students' math scores start increasing after the expected end of the regeneration and eventually catch up with control group scores. The same trend is evident for language, although the increase in treatment students' scores is lower in magnitude with respect to math.

I use the following DID specification to study the impact of regeneration programs on the achievement of local students:

$$Y_{icbsdt} = \alpha_0 + \alpha_1 D_{icbsd} \cdot T_t + \alpha_2 X_{icbsdt} + \gamma_s + \eta_b + \delta_t + u_c + e_{dt} + v_{icbsdt} \tag{3}$$

where $Y_{icbsdt}$ is math or language test score for student $i$ of cohort $c$ living in block $b$ and attending school $s$ in district $d$ at time $t$. $D_{icbsd}$ is the treatment dummy, and indicates whether there was a regeneration within 0.95 or 1.3km of school $s$ located in district $d$; $T_t$ is the 'post' dummy and takes a value of 1 from 3 years after a demolition, when the new building is expected to be completed. $\alpha_1$ is the main parameter of interest and identifies the effect of regenerations on the achievement of students attending local treated schools.

All regressions control for the number of schools in the treatment and control areas around the regeneration site, as well as quadratic polynomials in school enrolment and the number of children living in the block. $X_{icbsdt}$ is a vector of student controls including language spoken at home, ethnicity, gender, SEN, subsidized lunch eligibility, home-regeneration distance, home-school distance, an indicator for being moved as a result of the regeneration, and an indicator for being enrolled in an academy school.[18] As I also control for the students' baseline scores (KS1) in the relevant subject, estimates of $\alpha_1$ can be interpreted in terms of progress made

[18] Since I cannot link students directly to the building slated for regeneration, it is impossible to exactly identify those who have experienced some kind of 'exogenous' disruption – such as the moving due to the demolition – as a result of the program itself. Hence, I consider as 'moved by the regeneration' all children who leave a block where a regeneration occurs within one year (before and after) of its permission date. Considering those who leave only during the permission year instead does not change the results.

by each child or value-added provided by the treatment. $\gamma_s$, $\eta_b$, $u_c$, and $\delta_t$ are school, block, cohort and time fixed effects, respectively. Finally, in the most complete specification I add LA-specific time trends ($e_{dt}$) that are designed to capture general trends in school quality that may affect all schools participating in the same education 'market'. Standard errors are always clustered at school level.

Table 5 shows results from the estimation of equation (3) for math (Panel A) and language (Panel B). Every panel reports the standardized test score obtained in KS2 national tests in the relevant subject, as well as the level awarded according to the overall mark achieved in every test. Columns (1) to (3) present the results for the narrow sample, whereas columns (4) to (6) show the results for the loose sample.

Following the regeneration, students attending treated schools experience an increase in achievement of approximately 0.06$\sigma$ and 0.05$\sigma$ in math and language test scores, respectively, representing about 1 and 0.45 points or 1.5% of the sample average. All estimates are always significant at the 5% level. Overall, these initial results demonstrate that a (positive) externality generated by regeneration programs is an increase in the quality – declined as student achievement – in the schools surrounding the building targeted for regeneration.

In addition to the test mark achieved, I exploit as outcomes indicator variables for the test level achieved, focusing on Level 5 and Level 3 students or students achieving above and below the average, respectively. These outcomes are potentially more informative than the 'raw' test scores *per se* because they can be used to individuate which students benefit from the increase in test scores. For math scores, the estimates presented in the table imply that in the loose sample the fraction of students awarded Level 5 increases by about 1.6% in math (4.5% of the average), whereas the fraction of students awarded Level 3 decreases by roughly 1.5% (10% of the average). Coefficients obtained for the narrow sample are similar; Level 5 estimates are not significant, whereas Level 3 estimates are significant at 1% in the narrow and 5% in the loose sample. Coefficients obtained for language are also similar in magnitude, and significant at 1% in all but one instance. These estimates suggest that the increase in student achievement at the end of primary school happens across the board and benefits both students who would be achieving at the bottom of the distribution and (likely) those who would be achieving at the average of the distribution. However, the magnitudes implied by these coefficients also suggest that the benefits are more significant at the bottom of the distribution, where improvement relative to the average is double the size with respect to the top.

These results provide evidence that regeneration programs positively affect student achievement, and therefore school quality, in the surrounding neighborhood. The benefits accrue for both low- and average-performing children, showing that such programs have the potential of improving school quality for those students who would benefit more. These positive externalities – or spillovers – of public housing regenerations to local schools are often neglected in the public debate. The consequences of such short-term increases in school quality can potentially have long-lasting effects on local schools and the neighborhood. On one side, if marginal (possibly more affluent) families start moving into the area attracted by the increase in school quality, schools may experience a positive reinforcing mechanism leading to even larger increases in student achievement in the future (Battistin and Neri, 2017). On the other side, a further inflow of new, more affluent households *in the neighborhood* attracted by the increase in school quality, coupled with the increase in house prices, in the long-term might eventually lead to the displacement of local residents.

# 6 Regenerations and the Achievement of *Incumbent* Students

## Reduced form estimates

Estimates of $\alpha_1$ obtained from equation (3) do not represent the true impact of regenerations on *incumbent* students, i.e. students who were already attending treated schools at the time of a regeneration's completion. Over time, households may enter or leave the neighborhood and children will endogenously self-select into and out of its schools. Because of the nature of the programs and targeted neighborhoods, the direction of selection is *a priori* unclear. First, more affluent families possibly having high-achieving children and relocating to the new buildings might enroll their children in schools nearby. Second, low SES families living in the building slated for demolition might decide to leave the neighborhood – instead of relocating nearby – and therefore take their children out of local schools. In both cases, $\alpha_1$ may be picking up (positive) compositional effects and therefore be biased upward. Nonetheless, targeted neighborhoods still remain relatively more deprived (at least in the short-run) and some of the flats in the new buildings are still intended for low SES households, implying that over time schools can also face an inflow of negatively selected children, biasing $\alpha_1$ downwards.

Students who were originally attending the regeneration's neighboring schools are of particular interest from a policy perspective. Schools considered in this context predominantly serve more deprived neighborhoods and may therefore be locked in a bad equilibrium where there are few incentives to improve student achievement (Hastings et al., 2010). Additionally, more disadvantaged households may face barriers in exerting school choice anyway (such as high house prices close to high-quality schools, see, for instance, Black, 1999; Gibbons et al., 2013; Battistin and Neri, 2017). Possibly for this reason, the impact of school choice policies on student achievement has been shown to be quite limited (Cullen et al., 2005; Hastings et al., 2010; Deming et al., 2014).

However, early years education may have long lasting effects on future outcomes of children. Raising achievement during the early stages of a child's educational path can substantially improve medium- and long-term outcomes (Heckman, 2006); more educated children are more likely to enroll in college, and have better health and labor market outcomes (Deming, 2009; Chetty, 2011; Campbell et al., 2014). These issues gain even greater relevance in deprived neighborhoods, where the lack of good schools may mean that disadvantaged children struggle to obtain high-quality education.

In order to net out the effects of regeneration programs on incumbent students, I exploit an Instrumental Variable (IV) strategy for student enrolment in a treated school ($D$) using the fact that once children are enrolled in a given school, they have the right to retain their seat irrespective of whether they relocate from the original residence or new students enter their school's neighborhood. This motivates a 'grandfathering' instrument similar to the one developed by Abdulkadiroglu et al. (2016). The logic of this instrument lies in exploiting conditions in which parents' enrolment decisions are taken before a certain policy (such as conversion into a charter school, as in Abdulkadiroglu et al., 2016) affects the school chosen. As long as children have the right to maintain their school seat, they will be 'grandfathered' in the same school under the new policy.

The following reduced-form specification is therefore used to estimate the effect of regeneration programs on local incumbent students:

$$Y_{icbsdt} = \beta_0 + \beta_1 G_{icbsd} \cdot T_t + \beta_2 X_{icbsdt} + \gamma_s + \eta_b + \delta_t + u_c + e_{dt} + \varepsilon_{icbsdt} \quad (4)$$

where $G_{icbsd}$ is an indicator of enrolment in a school within 1.3km of a regeneration before its completion, i.e. 3 years after the permission date. Other variables follow the notation used in equation (3). In this framework, $\beta_1$ – representing the intent-to-treat (ITT) effect – identifies the causal effect of regeneration programs on incumbent children.

The underlying assumption is that parents could not anticipate the completion of the project or the effects it would have on local schools. Since regeneration projects considered here are mostly represented by large developments for which construction takes many years, it is very difficult for local residents to anticipate the final completion date. This simple intuition is indeed borne out by the data. Figure 8 depicts the evolution of the difference in a number of school characteristics over time between treated and control schools, showing that the composition of schools surrounding the regeneration programs does not change before the regeneration event. One may still worry that treated schools will attract better children *before* the regeneration itself. However, Figure 9 plots the difference in baseline student scores (KS1) between treatment and control students, showing that students did not select into treated schools based on their ability. These findings corroborate the fact that it was very challenging for families to anticipate the end of the program.

After the regeneration, incumbent students exhibit on average higher test scores in both math and language, as shown in Table 6. Standardized test scores increase by $0.04-0.06\sigma$, or roughly 1 and 0.6 points in math and language, respectively (about $1.5-1.9\%$ of the average). All estimates are significant at 5% except for language in the loose sample, significant at 1%. Similar to OLS estimates (Table 5), the increase in test scores appears to happen both at the bottom and the top of the distribution. For math, the fraction of students awarded Level 5 increases by about 2.6%, and the number of students awarded Level 3 decreases by 1.7%. As for OLS estimates, these figures imply larger effects at the bottom of the distribution, where the number of students awarded Level 3 decreases by more than 11% with respect to the average, compared to 7% at the top of the distribution. Point estimates for language follow a similar pattern. In the loose samples these latter estimates are always significant at 1%, with the exception of Level 5 math at 5%.

Table 7 further breaks down the effects of regenerations on standardized test scores into the four post periods (years) after the end of the program. These estimates are less precise but show that the increase in test scores begins immediately after the end of the regeneration; it increases over the first two years and then appears to flatten out or decrease slightly. However, this pattern should be interpreted with caution because the sample of regenerations is unbalanced over time (Figure 4). Figure 10 shows that, four years after the regeneration, the narrow sample only contains about $9,000$ students (200 schools), which represents about 70% of students and schools observed at the time of the program's completion (time = 3).

Figure 11 augments equation (4) with both leads and lags. Placebo coefficients estimated for standardized test scores before the end of the program are generally very close to zero and never significant. Pre-policy estimates for math scores are precisely estimated at zero; estimates for language seem a bit less precise but are always either negative or close to zero and never significant. Overall, the four graphs do not support the existence of any pre-trend in the outcomes considered. Point estimates after the program are instead positive and increasing for both subjects over the first two years, and follow the pattern outlined in Table 7.[19]

In conclusion, these results provide convincing evidence that public housing regeneration programs generate positive externalities that go beyond a 'simple' and direct increase in the quality of nearby schools. Students who were already attending a school surrounding a regeneration program – and therefore did not sort into them after that – benefit themselves in terms of educational achievement. This finding implies that, at least in the short-term, such programs can help raise the achievement of students in more deprived neighborhood. The effects in the long-term – as also briefly discussed in the previous section – are instead *a priori* unclear and will depend heavily on the extent of displacement that will possibly be generated if more affluent households start moving into the neighborhood, attracted by the increase in school quality.

## 2SLS Estimates of Regeneration Programs

Reduced form coefficients presented in Tables 6 and 7 can be interpreted as *intention-to-treat* (ITT) estimates. In other words, they assign to the treatment all children who were supposed to receive it irrespective of whether they then actually take it up. These estimates – together with first stage estimates of $D \cdot T$ on $G \cdot T$ – can be used to obtain the Local Average Treatment Effect (LATE), or the treatment effect on the treated. This latter parameter represents the causal effect of regeneration programs on the achievement of students attending local schools.

Table 8 (columns (1) and (6)) presents first stage results for the two samples where the interaction term $D \cdot T$ is instrumented with $G \cdot T$. Columns (1) and (6) show that on average, about $74-78\%$ of students remain in local schools following the regeneration. However, there is substantial variation over time. Columns (2) to (5) and (7) to (10) show results where the treatment indicator ($D$) as well as the grandfathering variable ($G$) are interacted with time-

[19]The same equation (4) with leads and lags can be estimated for the other outcomes considered in the analysis, namely the two indicator variables for being awarded Level 5 and Level 3. These outcomes follow the same patterns highlighted in Table 7 and Figure 11. The latter results are available upon request.

specific indicators for the four periods after the regeneration, and the former are instrumented with the latter; as expected, the effect decreases over time. After one year, between 89 and 90% of students taking KS2 tests were already in their school the previous year; after four years, the same fraction decreased to $74-79\%$.[20]

IV estimates of the causal effect of regeneration programs on student achievement are presented in Table 9. On average, the test scores of students attending a school within 1.3km of a regeneration increase by about $0.06\sigma$ and $0.08\sigma$, or 1.3 and 0.75 points, in math and language, respectively (about $1.9-2.5\%$ of the average). Consistently with Table 6, the increase in scores happens at both the bottom and the top of the distribution. The share of students awarded Level 5 in math increases by about 2% and the share of those awarded Level 3 decreases by approximately 1.5% (significant at 10% and 5%, respectively). Results for language are larger and always significant at the 1% level. The narrow sample exhibits a similar pattern.

2SLS estimates are slightly larger than the OLS estimates presented in Table 5 and are generally not statistically different from the latter. Despite the similar magnitude, the downward bias of OLS estimates might be due to a negative selection of students into the later grades in the schools surrounding the regeneration. One explanation is that as the neighborhoods studied are relatively more deprived and likely host a number of other public housing buildings, families relocating to the latter – and therefore more likely to have a more disadvantaged background – will eventually move their children to the local schools. As argued in Section 8, more affluent families relocating to the new buildings will not move their children if they are attending the later school grades to the local schools – as also shown by the minimal changes in school composition depicted in Figures 8 and 9. The implication of this finding is that any positive selection of students in the later primary school grades is unlikely to happen in the short-term.

## Heterogeneous Effects

The results presented in the last three sections mask substantial heterogeneity across different subgroups of children. In this Section, therefore, I study whether the effects found differ with

[20] These estimates are lower than other grandfathering estimates obtained for UK primary schools in other contexts. Eyles at al. (2017) exploit the grandfathering idea to study the effects of school conversion into academies on student performance, and their average estimate over the last four primary school years is that 93% of students enrolled in grade 3 remain in the school until grade 7. Further, Neri and Pasini (2018) have used a similar logic to study the effects of different governance models within academy schools and estimate that approximately 85% of 'grandfathered' students remain in the school after four years. However, both studies use a very selected sample of good or outstanding primary schools that decided voluntarily to become academies , meaning the samples are hardly comparable with the one used for the current study.

respect to a number of student characteristics, namely gender, country of origin, SES, and baseline scores. These heterogeneous effects are summarized in Figure 12.

The first finding of the subgroup analysis is that results do not appear to differ between female and male students. However, estimates happen to be stronger for non-native students, students eligible for subsidized lunches, and students with low or average baseline (KS1) scores. Hence, the more ethnically diverse and disadvantaged children are enjoying greater benefits from public housing regenerations, at least in terms of primary school achievement. These results highlight that such programs have, in the short-term, the potential to improve achievement in deprived areas by affecting those students who are likely to benefit more.

# 7 Summary of Main Robustness Tests

I carry out a number of robustness checks on the main specification (equation (4)); these are summarized in Table 10. First, I allow for LA-specific quadratic time trends (columns (1) and (5)). Second, I add a number of school level controls reflecting changes in school composition before and after the regeneration. The latter are school level averages of student characteristics (gender, origin, ethnicity, subsidized lunch eligibility, SEN, regeneration movers). The results from this augmented model are presented in columns (2) and (6). Finally, very large regenerations might be part of broader neighborhood programs and might include additional resources for new amenities (e.g., parks), schools, or business activities (e.g., shopping areas). Consequently, I exclude the top 5% (columns (3) and (7)) and 1% (columns (4) and (8)) of regeneration programs in terms of number of housing units built.

Estimates for both math and language and for both samples considered broadly reflect the results presented earlier in this section. 2SLS estimates including quadratic trends and school-level controls for composition are slightly larger than those presented in Table 9, and always significant at 1% level. Importantly, dropping from the sample very large regeneration programs (columns (3), (4), (7) and (8)) does not affect the estimates in any way. This result demonstrates that the findings obtained are not driven by large programs possibly carrying over additional large investment in local amenities and schools.

Finally, this study assesses whether the results are sensitive with respect to the choice of the control group. The *a priori* 'optimal' spacial width to consider for control students and schools is not clear; a control group that is too narrow can still be affected by spillovers, whereas a control group that considers schools and students located farther away may include units possibly very different from the treated ones and therefore not suitable for inclusion among the controls. Table 11 addresses this point by re-estimating equation (4), instrumenting $D \cdot T$ with $G \cdot T$ and considering different widths for the control group. The estimates are relatively stable across the different choices, both in terms of magnitude and significance, showing that the coefficients presented in Table 9 are not driven by the particular control group chosen.

# 8 Mediating Mechanisms

Because of the potential positive effects of regenerations on student achievement, in this Section I study what are the possible mechanisms mediating my results. I evaluate five possible explanations: positive peer effects within school grades due to (possibly higher-ability) new students moving into local schools; the disappearance of negative peer effects possibly due to negative selection of students leaving the schools surrounding the regenerations; neighborhood effects due to the appearance of new amenities linked to the regeneration (e.g., playgrounds built nearby) or to a decreases in crime rates (Aliprantis and Hartley, 2015; Sandler, 2017); changes in school inputs due to the regeneration; and changes in the composition of households' preferences due to more affluent households moving to the new building.

In this context, positive peer effects due to children of more affluent households moving into the new estate are not likely to play a big role. Even though over time one can observe a slight change in school composition, this happens only along the socio-economic dimension with a slight decrease in the number of children eligible for subsidized lunches after 4 years (Figure 8, Panel B). However, as previously demonstrated, school composition in terms of students' baseline achievement does not change (Figure 9). This suggests that positive effects stemming from higher ability children positively influencing their classmates are unlikely to be at play. This intuition is supported by the fact that affluent families moving into the newly constructed buildings and with children attending the later school grades do not tend to enroll them in local schools. This is shown in Figure 13, which plots the number of students not eligible for subsidised lunch enrolled in local schools after 4 and 3 years (orange and blue spikes, respectively) following the end of the regeneration process by grade of enrolment. Households moving into the new premises tend to enroll their children only in the initial school grades $(1-4)$, whereas enrolment in the later grades - grade 7 in particular - is close to zero. Hence, incumbent grade 7 students are unlikely to be exposed to the newcomers within their school grade.

The second type of peer effects at play might be due to the fact that students who over time leave the schools around the regeneration are negatively selected in terms of classroom behavior (e.g., classroom troublemakers) and therefore stop imposing this negative externality on their classmates. This hypothesis is evaluated again in Figure 8, Panel E, which plots the fraction of students eligible for SEN support within the last school grade before and after regeneration programs. As schools can place children with behavioral problems in special educational programs, SEN eligibility is used as a proxy for students with behavioral difficulties.[21]

A third type of peer effect that may be at play in this context is represented by neighborhood peer effects stemming from new amenities built as a result of the demolition. One example of this is children (incumbent and newcomers) interacting in the new facilities built within the regeneration programs, for instance new playgrounds. I therefore re-estimate equation (4), stratifying the sample according to the distance between each student's home and the regeneration. The intuition is that if the positive effects observed are driven by children's interactions due to new amenities built alongside the regeneration, one should observe larger effects for students living closer to the regeneration site (or possibly in the new building itself). Figure 14 plots the estimates obtained and shows that as one moves farther away from the regeneration the effects essentially remain constant. An alternative neighborhood effect could be represented by a decrease in crime rates around the regeneration after its completion. Figure 15 evaluates this possibility by estimating changes in the number of criminal offences by type of crime before and after a regeneration, and shows that the number of offences around the regeneration site did not change after its completion. These results suggests that 'direct' neighborhood effects driven by the regeneration itself are also unlikely to play a substantial role in this context.

Another possible explanation is that schools surrounding a regeneration enjoy an increase in several inputs to cope with the possible increase in the number of students. Table 12 addresses this possibility by exploiting two school-level input measures: funding (Panel A) and teachers (Panel B). Panel A shows that funding assigned to schools surrounding the regeneration does not increase along any dimension (total funding, funding for teachers and other staff, and for learning resources). Consistent with Panel A, staff structure (Panel B) also does not change,

[21] Schools can place students requiring special supports along certain dimensions in two programs, School Action (SA) and School Action Plus (SA+). Students with more serious needs (such as visual impairments or disabilities) are instead granted support by LAs themselves and are usually given a 'statement' of SEN. The latter category, however, accounts for only about 10% of all students eligible for some form of SEN support.

providing evidence that regenerations are not accompanied by adjustments in school inputs.

Finally, I evaluate the role of household preferences. Hastings et al. (2010) have noted that more deprived households exhibit very strong preferences for school distance rather than school quality, whereas more affluent households have a strong preference for the latter. The main consequence is that schools located in more disadvantaged neighborhoods can act as 'local monopolists', and have very few incentives to improve their quality and increase student achievement. However, the inflow of more affluent households relocating to the newly built premises may drive changes in the local school market, eventually benefiting incumbent students as well.

As more affluent households enter the neighborhood relocating to the new premises, they will start demanding better schools for their children. Indeed, despite the possibility of enrolling their children in schools with looser requirements in terms of distance (e.g., faith schools), the vast majority of state-funded schools (academies included) do prioritize children based on distance; moreover, as noted, 80% of children attend a school which is within 1.3km of their residence. This intuition is confirmed by Figure 13, which shows that affluent families relocating to the new building do enroll their children in local schools if the latter have to attend the $1^{st}$ grade. This process may lead to demand-driven changes in school practices that cannot be observed within the available data. For example, headteachers might organize extra activities for children (such as afternoon study) or demand more from their teachers. Additionally, some headteachers might have the incentive to attract the new incoming children in order to increase the average 'quality' of the pupil intake or the school roll itself, and could therefore implement a number of school practices in order to increase the quality – and therefore the attractiveness – of their school.

# 9 Conclusion

A growing literature suggests that neighborhoods extensively affect children's future outcomes through neighborhood exposure. However, the specific mechanism driving these effects are not well understood yet. In this paper I study how an inflow of more affluent households to a neighborhood affects short-term schooling outcomes of children already living in the neighborhood. I address this issue by exploiting public housing regenerations in London, which led to the creation of thousands of new homes in more deprived neighborhoods that were mostly targeted by wealthier households. When it comes to regeneration programs targeting public housing buildings and involving their demolition and subsequent reconstruction of brand-new buildings, local councils are often accused of pursuing social cleansing and thereby increasing residential segregation. I first show that in the short-term these programs generated little displacement of public housing residents from the neighborhood and children from local schools.

A DID analysis reveals that a positive externality of public housing regenerations is an increase in the quality – declined as student achievement – of primary schools located nearby. Exploiting an IV strategy, this study provides evidence that this externality is not due to a compositional effect; instead, students originally attending a school close to a regeneration before its completion enjoy substantial benefits in terms of educational achievement at the end of primary school. Interestingly, students from a low socio-economic background and with low baseline scores are those benefiting more from the regenerations.

My findings highlight that rather than generating residential segregation, in the short-term these programs have the potential to drive positive externalities for local children in terms of achievement. However, the same programs also drive a substantial increase in house prices over the subsequent four years, making the neighborhood potentially less affordable for poorer households. The latter finding, together with a growing body of literature showing that more affluent households tend to target areas with good schools, suggests that in the medium- to long-run the area surrounding the regeneration could be targeted by richer households that will eventually drive incumbent residents out.

As a final note, one mechanism that is likely to play an important role in this context is represented by the change in household preferences due to the arrival of more affluent households exhibiting stronger preferences for school quality. This highlights that having more 'mixed' neighborhoods may introduce substantial benefits for children as those growing up in more deprived neighborhoods will struggle to obtain high-quality education. However, with the available data it is hard to pin down exactly the extent of this channel. I hope to address this issue in future research.

# References

Abdulkadiroğlu, A., Angrist, J. D., Hull, P. D., and Pathak, P. A. (2016). Charters without lotteries: testing takeovers in New Orleans and Boston. *The American Economic Review*, 106(7):1878–1920.

Aliprantis, D. and Hartley, D. (2015). Blowing it up and knocking it down: The local and city-wide effects of demolishing high concentration public housing on crime. *Journal of Urban Economics*, 88:67–81.

Battistin, E. and Neri, L. (2017). School performance, score inflation and economic geography. *IZA Discussion Paper No. 11161*.

Bergman, P., Chetty, R., DeLuca, S., Hendren, N., Katz, L. F., and Palmer, C. (2019). Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. *NBER Working Paper No. 26164*.

Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *The Quarterly Journal of Economics*, 114(2):577–599.

Campbell, F., Conti, G., Heckman, J. J., Moon, S. H., Pinto, R., Pungello, E., and Pan, Y. (2014). Early childhood investments substantially boost adult health. *Science*, 343(6178):1478–1485.

Chetty, R., Friedman, J., Hilger, N., Saez, E., Schanzenbach, D., and Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from project star. *Quarterly Journal of Economics*, 126(4):1593–1660.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

Chyn, E. (2018). Moved to opportunity: The long-run effects of public housing demolition on children. *American Economic Review*, 108(10):3028–3056.

Cullen, J. B., Jacob, B. A., and Levitt, S. D. (2005). The impact of school choice on student outcomes: an analysis of the chicago public schools. *Journal of Public Economics*, 89:729–760.

Deming, D. (2009). Early childhood intervention and life-cycle skill development: evidence from Head Start. *American Economic Journal: Applied Economics*, 1(3):111–134.

Deming, D. J., Hastings, J. S., Kane, T. J., and Staiger, D. O. (2014). School choice, school quality, and postsecondary attainment. *American Economic Review*, 104(3):991–1013.

Diamond, R. and McQuade, T. (2019). Who wants affordable housing in their backyard? an equilibrium analysis of low income property development. *Journal of Political Economy*, 27:3:1063–1117.

Eyles, A., Machin, S., and McNally, S. (2017). Unexpected school reform: academisation of primary schools in England. *Journal of Public Economics*, 155:108–121.

Gibbons, S., Machin, S., and Silva, O. (2013). Valuing school quality using boundary discontinuity regressions. *Journal of Urban Economics*, 75(1):15–28.

Hastings, J. S., Kane, T. J., and Staiger, D. O. (2010). Heterogeneous preferences and the efficacy of public school choice. *Working Paper*.

Heckman, J. J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science*, 312(5782):1900–1902.

Jacob, B. A. (2004). Public housing, housing vouchers, and student achievement: Evidence from public housing demolitions in Chicago. *American Economic Review*, 94(1):233–258.

Jacob, B. A., Kapustin, M., and Ludwig, J. (2015). The impact of housing assistance on child outcomes: Evidence from a randomized housing lottery. *The Quarterly Journal of Economics*, page 465–506.

Jacob, B. A. and Ludwig, J. (2012). The effects of housing assistance on labor supply: Evidence from a voucher lottery. *American Economic Review*, 102(1):272–304.

Koster, H. R. A. and Ommeren, J. (2018). Place-based policies and the housing market. *Review of Economics and Statistics*.

Lalibertè, J. P. (2018). Long-term contextual effects in education: Schools and neighborhoods. *Unpublished manuscript*.

Mayor of London (2018). Better homes for local people. The mayor's good practice guide to estate regeneration.

Neri, L. and Pasini, E. (2018). Heterogeneous effects of mass academisation in england. *School of Economics and Finance WP 847, Queen Mary University of London*.

Oreopoulos, P. (2003). The long-run consequences of living in a poor neighborhood. *The Quarterly Journal of Economics*, 118(4):1533–1575.

Rossi-Hansberg, E., Sarte, P. D., and Owens III, R. (2010). Housing externalities. *Journal of Political Economy*, 118(3).

Sandler, D. H. (2017). Externalities of public housing: The effect of public housing demolitionson local crime. *Regional Science and Urban Economics*, 62:24–35.

van Dijk, W. (2019). The socio-economic consequences of housing assistance. *Unpublished manuscript*.

## Table 1. Households living in public housing

| | Households living in: | | | Blocks: | | |
|---|---|---|---|---|---|---|
| | Greater London | Private housing | Public housing | Without regeneration | With regeneration | Final sample |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Census (2001)** | | | | | | |
| Percent white | 0.77 | 0.80 | 0.68 | | | |
| Percent black | 0.11 | 0.07 | 0.21 | | | |
| Percent asian | 0.08 | 0.11 | 0.07 | | | |
| Percent managers | 0.44 | 0.49 | 0.21 | 0.44 | 0.38 | 0.38 |
| Percent low skilled | 0.20 | 0.17 | 0.33 | 0.20 | 0.23 | 0.24 |
| Percent unemployed | 0.05 | 0.03 | 0.14 | 0.05 | 0.08 | 0.08 |
| Percent with no car | 0.37 | 0.30 | 0.60 | 0.36 | 0.48 | 0.48 |
| Percent with no qualification | 0.26 | | | 0.26 | 0.31 | 0.31 |
| Percent high qualified | 0.32 | | | 0.32 | 0.30 | 0.29 |
| **Panel B: National Pupil Database (2002)** | | | | | | |
| Percent male | 0.51 | | | 0.51 | 0.52 | 0.51 |
| Percent white | 0.58 | | | 0.58 | 0.48 | 0.55 |
| Percent black | 0.19 | | | 0.19 | 0.25 | 0.25 |
| Percent asian | 0.13 | | | 0.13 | 0.17 | 0.09 |
| Percent native | 0.28 | | | 0.68 | 0.60 | 0.65 |
| Deprivation score | 0.68 | | | 0.28 | 0.43 | 0.42 |
| Percent eligible for subsidised lunch | 0.25 | | | 0.25 | 0.38 | 0.37 |
| Percent with SEN | 0.17 | | | 0.17 | 0.19 | 0.19 |
| Number of blocks | 4,765 | | | 4,630 | 135 | 39 |

**Note**. The table shows descriptive statistics for households living in Greater London (column (1)), private housing (column (2)), public housing (column (3)), blocks without a regeneration program (column (4)), blocks with a regeneration program (column (5)), and blocks of regenerations in the final sample (column (6)). Private housing includes households living in owned, privately rented and rent free accommodation; public housing includes households living in accommodation provided by local councils or housing associations. Column (5) uses regenerations whose permission date is between 2004 and 2013 and with at at least 10 housing units in the new building. The number of blocks (135) is lower than the number of regenerations stated in the main text (145) because in this initial sample some regenerations occur in the same block. Panel A uses data from the 2001 Census for the population, whereas Panel B uses data from the National Pupil Database in 2002 for all children aged 4-11 enrolled in state-funded schools. Data on ethnicity by type of tenancy at block level, and on qualifications and children by type of tenancy are not available.

## Table 2. Descriptive statistics

| | Narrow sample | | Loose sample | |
|---|---|---|---|---|
| | mean | S.D. | mean | S.D. |
| | (1) | (2) | (3) | (3) |
| | | **Panel A. Houses** | | |
| House price | 436,452.90 | 471,824.40 | 442,742.80 | 479,951.50 |
| Percent detached | 0.0260 | 0.1592 | 0.0267 | 0.1612 |
| Percent semi-detached | 0.1132 | 0.3169 | 0.1119 | 0.3153 |
| Percent terraced | 0.2758 | 0.4469 | 0.2694 | 0.4436 |
| Percent flat | 0.5849 | 0.4927 | 0.5920 | 0.4915 |
| Percent new | 0.0831 | 0.2760 | 0.0806 | 0.2722 |
| | | **Panel B. Students** | | |
| Academy enrollment | 0.0270 | 0.1621 | 0.0263 | 0.1601 |
| Native | 0.5564 | 0.4968 | 0.5524 | 0.4972 |
| White | 0.3997 | 0.4898 | 0.3941 | 0.4887 |
| Black | 0.2852 | 0.4515 | 0.2917 | 0.4546 |
| Asian | 0.1709 | 0.3764 | 0.1687 | 0.3745 |
| Male | 0.5026 | 0.5000 | 0.5034 | 0.5000 |
| On subsidised lunch | 0.3056 | 0.4606 | 0.3107 | 0.4628 |
| With special educational needs (SEN) | 0.2575 | 0.4373 | 0.2607 | 0.4390 |
| | | **Panel C. Student achievement** | | |
| Above expected level at KS1 (math) | 0.1882 | 0.3909 | 0.1847 | 0.3880 |
| Below expected level at KS1 (math) | 0.1203 | 0.3253 | 0.1221 | 0.3274 |
| Above expected level at KS1 (language) | 0.2130 | 0.4094 | 0.2100 | 0.4073 |
| Below expected level at KS1 (language) | 0.1779 | 0.3824 | 0.1815 | 0.3854 |
| Math score | 67.24 | 21.58 | 67.05 | 21.59 |
| Language score | 29.80 | 9.27 | 29.76 | 9.26 |
| Above expected level at KS2 (math) | 0.3664 | 0.4818 | 0.3632 | 0.4809 |
| Below expected level at KS2 (math) | 0.1483 | 0.3554 | 0.1497 | 0.3568 |
| Above expected level at KS2 (language) | 0.3553 | 0.4786 | 0.3529 | 0.4779 |
| Below expected level at KS2 (language) | 0.1196 | 0.3245 | 0.1205 | 0.3255 |
| | | **Panel D. Schools** | | |
| Percent SEN | 0.2716 | 0.1285 | 0.2751 | 0.1318 |
| Percent on subsidised lunch | 0.3089 | 0.1783 | 0.3141 | 0.1755 |
| Percent black | 0.2851 | 0.2107 | 0.2917 | 0.2101 |
| Percent natives | 0.5593 | 0.2532 | 0.5553 | 0.2497 |
| Percent white | 0.4018 | 0.2618 | 0.3960 | 0.2563 |
| Percent asian | 0.1695 | 0.2158 | 0.1673 | 0.2095 |
| Percent male | 0.5046 | 0.0779 | 0.5053 | 0.0787 |
| Average std KS1 point score | -0.0328 | 0.3542 | -0.0453 | 0.3531 |
| Enrolment | 51.48 | 20.39 | 50.50 | 20.11 |
| Number of transactions | 251,176 | | 384,991 | |
| Number of students | 142,451 | | 179,835 | |
| Number of schools | 310 | | 405 | |

**Note**.The table presents summary statistics for the narrow sample (columns (1) and (2)) and loose sample (columns (3) and (4)) for houses (Panel A), student characteristics (Panel B), student achievement (Panel C), and school characteristics (Panel D). Prices are in 2018 figures.

## Table 3. Effects of regeneration programs on house prices

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A. Average Effect** | | | | | |
| Treated * post | 0.024 | 0.017 | 0.017 | 0.019 | 0.012 | 0.012 |
| | (0.004) | (0.004) | (0.004) | (0.002) | (0.003) | (0.003) |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| | **Panel B. Time-specific Effect** | | | | | |
| *Treatment effect after:* | | | | | | |
| One year | 0.020 | 0.016 | 0.015 | 0.013 | 0.008 | 0.007 |
| | (0.005) | (0.005) | (0.005) | (0.003) | (0.004) | (0.004) |
| | [0.000] | [0.002] | [0.005] | [0.000] | [0.024] | [0.037] |
| Two years | 0.023 | 0.014 | 0.013 | 0.019 | 0.009 | 0.008 |
| | (0.005) | (0.006) | (0.006) | (0.004) | (0.004) | (0.004) |
| | [0.000] | [0.017] | [0.028] | [0.000] | [0.019] | [0.032] |
| Three years | 0.025 | 0.016 | 0.017 | 0.022 | 0.013 | 0.014 |
| | (0.005) | (0.006) | (0.006) | (0.004) | (0.004) | (0.004) |
| | [0.000] | [0.007] | [0.005] | [0.000] | [0.001] | [0.001] |
| Four years | 0.030 | 0.024 | 0.023 | 0.025 | 0.020 | 0.019 |
| | (0.006) | (0.006) | (0.007) | (0.004) | (0.004) | (0.004) |
| | [0.000] | [0.000] | [0.001] | [0.000] | [0.000] | [0.000] |
| House controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Postcode FE | No | Yes | Yes | No | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | No | Yes | Yes | No |
| Month FE | Yes | Yes | No | Yes | Yes | No |
| Year * month FE | No | No | Yes | No | No | Yes |
| Observations | 251,176 | 251,176 | 251,176 | 384,991 | 384,991 | 384,991 |

**Note**. The table shows the effects of regeneration programs on the (log) price paid for houses located within 0.95km (columns (1) to (3)), and 1.3km (columns (4) to (6)). Panel A shows the average effect up to four years after the end of the construction; Panel B shows time-specific effects. All columns control for house type (detached, semi-detached, terraced, flat), age (newly built), contract type (freehold or leasehold), and time fixed effects. Columns (1) and (4) add year and month fixed effects; columns (2) and (5) add year and month fixed effects; columns (3) and (6) use year*month fixed effects instead of separate fixed effects for year and month. Standard errors, shown in brackets, are clustered on postcodes. P-values are shown in square brackets.

## Table 4. Descriptive statistics for narrow and loose samples

| | Treatment | | | | Control | |
|---|---|---|---|---|---|---|
| | Narrow sample | | Loose sample | | | |
| | mean | S.D. | mean | S.D. | mean | S.D. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A. Students** | | | | | | |
| Academy enrolment | 0.0380 | 0.1913 | 0.0328 | 0.1782 | 0.0176 | 0.1317 |
| Native | 0.5419 | 0.4982 | 0.5403 | 0.4984 | 0.5687 | 0.4953 |
| White | 0.3708 | 0.4830 | 0.3715 | 0.4832 | 0.4243 | 0.4942 |
| Black | 0.3215 | 0.4671 | 0.3197 | 0.4664 | 0.2543 | 0.4355 |
| Asian | 0.1570 | 0.3638 | 0.1582 | 0.3649 | 0.1828 | 0.3865 |
| Male | 0.5004 | 0.5000 | 0.5025 | 0.5000 | 0.5045 | 0.5000 |
| On subsidised lunch | 0.3528 | 0.4778 | 0.3445 | 0.4752 | 0.2653 | 0.4415 |
| With special educational needs (SEN) | 0.2799 | 0.4489 | 0.2773 | 0.4477 | 0.2384 | 0.4261 |
| **Panel B. Student achievement** | | | | | | |
| Above expected level at KS1 (math) | 0.1671 | 0.3731 | 0.1686 | 0.3744 | 0.2065 | 0.4048 |
| Below expected level at KS1 (math) | 0.1344 | 0.3411 | 0.1325 | 0.3390 | 0.1080 | 0.3104 |
| Above expected level at KS1 (language) | 0.1891 | 0.3916 | 0.1927 | 0.3944 | 0.2336 | 0.4231 |
| Below expected level at KS1 (language) | 0.1941 | 0.3955 | 0.1945 | 0.3958 | 0.1639 | 0.3702 |
| Math score | 65.79 | 21.78 | 65.99 | 21.72 | 68.47 | 21.33 |
| Language score | 29.29 | 9.25 | 29.41 | 9.24 | 30.24 | 9.26 |
| Above expected level at KS2 (math) | 0.3386 | 0.4732 | 0.3430 | 0.4747 | 0.3902 | 0.4878 |
| Below expected level at KS2 (math) | 0.1601 | 0.3667 | 0.1583 | 0.3651 | 0.1382 | 0.3451 |
| Above expected level at KS2 (language) | 0.3324 | 0.4711 | 0.3365 | 0.4725 | 0.3747 | 0.4841 |
| Below expected level at KS2 (language) | 0.1296 | 0.3358 | 0.1274 | 0.3334 | 0.1112 | 0.3144 |
| **Panel C. Schools** | | | | | | |
| Percent SEN | 0.2954 | 0.1356 | 0.2928 | 0.1384 | 0.2514 | 0.1183 |
| Percent on subsidised lunch | 0.3564 | 0.1630 | 0.3481 | 0.1633 | 0.2685 | 0.1809 |
| Percent black | 0.3210 | 0.1995 | 0.3196 | 0.2019 | 0.2545 | 0.2150 |
| Percent natives | 0.5452 | 0.2299 | 0.5434 | 0.2319 | 0.5713 | 0.2709 |
| Percent white | 0.3735 | 0.2366 | 0.3736 | 0.2353 | 0.4259 | 0.2792 |
| Percent asian | 0.1551 | 0.1842 | 0.1566 | 0.1837 | 0.1817 | 0.2388 |
| Percent male | 0.5029 | 0.0803 | 0.5047 | 0.0808 | 0.5060 | 0.0758 |
| Average std KS1 point score | -0.1037 | 0.3314 | -0.0999 | 0.3363 | 0.0276 | 0.3617 |
| Enrolment | 48.02 | 19.26 | 47.56 | 19.02 | 54.43 | 20.85 |
| Number of students | 65,540 | | 102,924 | | 76,911 | |

**Note**. The table shows summary statistics for students (Panel A), student achievement (Panel B), and schools (Panel C) separately for the treatment samples (columns (1) to (4)) and control sample (columns (5) and (6)). Columns (1) and (2) considers all students attending a school located within 0.95km from a regeneration; columns (3) and (4) considers all students attending a school located within 1.3km from a regeneration. Control students (columns (5) and (6)) are all students attending a school within 1.3 and 2km from the regeneration.

Table 5. OLS estimates of regeneration programs on student achievement

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A: Math scores** | | | | | |
| Test score | 0.096 | 0.091 | 0.073 | 0.070 | 0.072 | 0.050 |
| | (0.031) | (0.031) | (0.031) | (0.028) | (0.028) | (0.027) |
| | [0.002] | [0.003] | [0.019] | [0.014] | [0.010] | [0.064] |
| Achieved Level 5 | 0.032 | 0.029 | 0.020 | 0.024 | 0.025 | 0.016 |
| | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) |
| | [0.010] | [0.017] | [0.102] | [0.035] | [0.026] | [0.139] |
| Achieved Level 3 | -0.030 | -0.029 | -0.025 | -0.021 | -0.021 | -0.015 |
| | (0.008) | (0.008) | (0.008) | (0.007) | (0.007) | (0.007) |
| | [0.000] | [0.000] | [0.002] | [0.005] | [0.004] | [0.034] |
| | **Panel B: Language scores** | | | | | |
| Test score | 0.076 | 0.077 | 0.063 | 0.072 | 0.080 | 0.064 |
| | (0.030) | (0.029) | (0.030) | (0.026) | (0.025) | (0.025) |
| | [0.012] | [0.007] | [0.034] | [0.007] | [0.001] | [0.009] |
| Achieved Level 5 | 0.035 | 0.034 | 0.028 | 0.033 | 0.035 | 0.028 |
| | (0.013) | (0.012) | (0.013) | (0.011) | (0.011) | (0.011) |
| | [0.005] | [0.007] | [0.038] | [0.003] | [0.001] | [0.009] |
| Achieved Level 3 | -0.021 | -0.023 | -0.021 | -0.020 | -0.022 | -0.019 |
| | (0.007) | (0.007) | (0.007) | (0.006) | (0.006) | (0.006) |
| | [0.003] | [0.001] | [0.002] | [0.001] | [0.000] | [0.001] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | No | Yes | Yes | No | Yes | Yes |
| LA-specific time trends | No | No | Yes | No | No | Yes |
| Observations | 142,451 | 142,451 | 142,451 | 179,835 | 179,835 | 179,835 |

**Note**. The table shows OLS regressions of math (Panel A) and language (Panel B) scores on the occurrence of a regeneration program within 0.95km (columns (1) to (3)) and within 1.3km (columns (4) to (6)) from the school of attendance. Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), and school, cohort, time, and child's block fixed effects. Columns (2) and (5) add student scores at baseline (KS1); columns (3) and (6) add LA-specific time trends. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

## Table 6. Reduced form estimates of regeneration programs on student achievement

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A: Math scores** | | | | | |
| Test score | 0.099 | 0.075 | 0.059 | 0.081 | 0.062 | 0.043 |
| | (0.024) | (0.024) | (0.023) | (0.021) | (0.021) | (0.019) |
| | [0.000] | [0.002] | [0.011] | [0.000] | [0.003] | [0.026] |
| Achieved Level 5 | 0.034 | 0.025 | 0.017 | 0.038 | 0.031 | 0.026 |
| | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) |
| | [0.001] | [0.010] | [0.067] | [0.000] | [0.002] | [0.015] |
| Achieved Level 3 | -0.026 | -0.021 | -0.017 | -0.021 | -0.018 | -0.017 |
| | (0.007) | (0.006) | (0.006) | (0.006) | (0.005) | (0.006) |
| | [0.000] | [0.001] | [0.005] | [0.000] | [0.001] | [0.003] |
| | **Panel B: Language scores** | | | | | |
| Test score | 0.085 | 0.070 | 0.057 | 0.084 | 0.073 | 0.059 |
| | (0.023) | (0.023) | (0.023) | (0.020) | (0.019) | (0.018) |
| | [0.000] | [0.002] | [0.013] | [0.000] | [0.000] | [0.001] |
| Achieved Level 5 | 0.029 | 0.022 | 0.015 | 0.036 | 0.031 | 0.026 |
| | (0.009) | (0.009) | (0.008) | (0.008) | (0.008) | (0.008) |
| | [0.001] | [0.009] | [0.065] | [0.000] | [0.000] | [0.002] |
| Achieved Level 3 | -0.020 | -0.016 | -0.011 | -0.021 | -0.019 | -0.017 |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| | [0.001] | [0.006] | [0.045] | [0.000] | [0.000] | [0.000] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | No | Yes | Yes | No | Yes | Yes |
| LA-specific time trends | No | No | Yes | No | No | Yes |
| Observations | 142,451 | 142,451 | 142,451 | 179,835 | 179,835 | 179,835 |

**Note.** The table shows reduced-form regressions of math (Panel A) and language (Panel B) scores on the grandfathering interaction considering students attending a school within 0.95km (columns (1) to (3)) and within 1.3km (columns (4) to (6)) from a regeneration program. Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), and school, cohort, time, and child's block fixed effects. Columns (2) and (5) add student scores at baseline (KS1); columns (3) and (6) add LA-specific time trends. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

Table 7. Reduced form estimates of regeneration programs on student achievement over time

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A: Math scores** | | | | | |
| One year | 0.064 | 0.032 | 0.020 | 0.083 | 0.067 | 0.058 |
| | (0.032) | (0.032) | (0.031) | (0.033) | (0.032) | (0.033) |
| | [0.046] | [0.316] | [0.517] | [0.012] | [0.040] | [0.076] |
| Two years | 0.118 | 0.116 | 0.097 | 0.114 | 0.104 | 0.089 |
| | (0.031) | (0.031) | (0.030) | (0.030) | (0.029) | (0.029) |
| | [0.000] | [0.000] | [0.001] | [0.000] | [0.000] | [0.003] |
| Three years | 0.097 | 0.073 | 0.058 | 0.067 | 0.061 | 0.049 |
| | (0.038) | (0.036) | (0.035) | (0.036) | (0.034) | (0.034) |
| | [0.010] | [0.041] | [0.098] | [0.065] | [0.073] | [0.155] |
| Four years | 0.129 | 0.088 | 0.067 | 0.074 | 0.042 | 0.025 |
| | (0.035) | (0.034) | (0.034) | (0.036) | (0.036) | (0.036) |
| | [0.000] | [0.011] | [0.051] | [0.044] | [0.246] | [0.489] |
| | **Panel B: Language scores** | | | | | |
| One year | 0.038 | 0.015 | -0.001 | 0.078 | 0.069 | 0.058 |
| | (0.029) | (0.028) | (0.027) | (0.027) | (0.026) | (0.026) |
| | [0.185] | [0.609] | [0.983] | [0.005] | [0.010] | [0.027] |
| Two years | 0.093 | 0.097 | 0.076 | 0.107 | 0.108 | 0.092 |
| | (0.029) | (0.028) | (0.026) | (0.026) | (0.026) | (0.025) |
| | [0.001] | [0.001] | [0.004] | [0.000] | [0.000] | [0.000] |
| Three years | 0.090 | 0.065 | 0.046 | 0.075 | 0.063 | 0.048 |
| | (0.032) | (0.031) | (0.030) | (0.031) | (0.029) | (0.029) |
| | [0.006] | [0.036] | [0.130] | [0.018] | [0.030] | [0.095] |
| Four years | 0.115 | 0.081 | 0.063 | 0.077 | 0.048 | 0.033 |
| | (0.032) | (0.032) | (0.031) | (0.032) | (0.031) | (0.030) |
| | [0.000] | [0.012] | [0.041] | [0.015] | [0.127] | [0.279] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | No | Yes | Yes | No | Yes | Yes |
| LA-specific time trends | No | No | Yes | No | No | Yes |
| Observations | 142,451 | 142,451 | 142,451 | 179,835 | 179,835 | 179,835 |

**Note**. The table shows reduced-form regressions of math (Panel A) and language (Panel B) scores on the grandfathering indicator interacted with time-specific dummies for the four years after the regeneration. Columns (1) to (3) consider all students attending a school located within 0.95km from a regeneration; columns (4) to (6) consider all students attending a school located within 1.3km from a regeneration. Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), and school, cohort, time, and child's block fixed effects. Columns (2) and (5) add student scores at baseline (KS1); columns (3) and (6) add LA-specific time trends. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

# Table 8. First stage estimates

| | Narrow sample | | | | | Loose sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Treated * post | Treated after: | | | | Treated * post | Treated after: | | | |
| | | One year | Two years | Three years | Four years | | One year | Two years | Three years | Four years |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Grandfathered * post | 0.784 | | | | | 0.752 | | | | |
| | (0.011) | | | | | (0.015) | | | | |
| | [0.000] | | | | | [0.000] | | | | |
| *Grandfathered after:* | | | | | | | | | | |
| One year | | 0.902 | -0.023 | -0.025 | -0.024 | | 0.887 | -0.023 | -0.026 | -0.026 |
| | | (0.006) | (0.002) | (0.002) | (0.002) | | (0.008) | (0.001) | (0.002) | (0.002) |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] | [0.000] | [0.000] | [0.000] |
| Two years | | -0.017 | 0.862 | -0.026 | -0.027 | | -0.018 | 0.839 | -0.028 | -0.029 |
| | | (0.001) | (0.009) | (0.002) | (0.002) | | (0.001) | (0.012) | (0.002) | (0.002) |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] | [0.000] | [0.000] | [0.000] |
| Three years | | -0.017 | -0.024 | 0.838 | -0.028 | | -0.017 | -0.024 | 0.801 | -0.029 |
| | | (0.001) | (0.002) | (0.012) | (0.002) | | (0.001) | (0.001) | (0.016) | (0.002) |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] | [0.000] | [0.000] | [0.000] |
| Four years | | -0.015 | -0.023 | -0.026 | 0.790 | | -0.016 | -0.023 | -0.027 | 0.741 |
| | | (0.002) | (0.002) | (0.002) | (0.015) | | (0.001) | (0.001) | (0.002) | (0.021) |
| | | [0.000] | [0.000] | [0.000] | [0.000] | | [0.000] | [0.000] | [0.000] | [0.000] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA-specific time trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 142,451 | 142,451 | 142,451 | 142,452 | 142,453 | 179,835 | 179,836 | 179,837 | 179,838 | 179,839 |

**Note**. The table shows first stage regressions of the occurrence of a regeneration program (DT) on the grandfathering interaction (GT) for all students attending a school within 0.95km (columns (1) to (5)) and within 1.3km (columns (6) to (10)) from a regeneration. Columns (1) and (6) consider the interaction of the grandfathering indicator with an indicator variable for all years after the regeneration. Columns (2) to (5) and (7) to (10) consider the interaction of the grandfathering indicator with four time-specific dummies, one for every year after the regeneration. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), student scores at baseline (KS1), LA-specific time trends and school, cohort, time, and child's block fixed effects. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

Table 9. 2SLS estimates of regeneration programs on student achievement

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A: Math scores** | | | | | |
| Math test scores | 0.127 | 0.096 | 0.077 | 0.107 | 0.082 | 0.059 |
| | (0.031) | (0.031) | (0.030) | (0.029) | (0.028) | (0.026) |
| | [0.000] | [0.002] | [0.011] | [0.000] | [0.003] | [0.026] |
| Achieved Level 5 | 0.044 | 0.032 | 0.023 | 0.039 | 0.030 | 0.020 |
| | (0.013) | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) |
| | [0.001] | [0.010] | [0.067] | [0.001] | [0.010] | [0.065] |
| Achieved Level 3 | -0.033 | -0.027 | -0.023 | -0.026 | -0.021 | -0.015 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.007) | (0.007) |
| | [0.000] | [0.001] | [0.005] | [0.001] | [0.006] | [0.044] |
| | **Panel B: Language scores** | | | | | |
| Math test scores | 0.109 | 0.089 | 0.075 | 0.112 | 0.098 | 0.081 |
| | (0.030) | (0.029) | (0.030) | (0.027) | (0.025) | (0.025) |
| | [0.000] | [0.002] | [0.013] | [0.000] | [0.000] | [0.001] |
| Achieved Level 5 | 0.049 | 0.040 | 0.034 | 0.047 | 0.041 | 0.035 |
| | (0.013) | (0.013) | (0.014) | (0.011) | (0.011) | (0.011) |
| | [0.000] | [0.002] | [0.015] | [0.000] | [0.000] | [0.002] |
| Achieved Level 3 | -0.026 | -0.024 | -0.022 | -0.028 | -0.026 | -0.023 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.006) |
| | [0.000] | [0.001] | [0.003] | [0.000] | [0.000] | [0.000] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | No | Yes | Yes | No | Yes | Yes |
| LA-specific time trends | No | No | Yes | No | No | Yes |
| Observations | 142,451 | 142,451 | 142,451 | 179,835 | 179,835 | 179,835 |

**Note**. The table shows 2SLS regressions of math (Panel A) and language (Panel B) scores on the occurrence of a regeneration program within 0.95km (columns (1) to (3)) and within 1.3km (columns (4) to (6)) from the school of attendance. Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), and school, cohort, time, and child's block fixed effects. Columns (2) and (5) add student scores at baseline (KS1); columns (3) and (6) add LA-specific time trends. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

## Table 10. Robustness checks: different sets of controls

| | Sample: | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Narrow | | | | Loose | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | **Panel A: Math scores** | | | | | | | |
| Test score | 0.084 | 0.088 | 0.090 | 0.088 | 0.066 | 0.063 | 0.074 | 0.062 |
| | (0.030) | (0.028) | (0.029) | (0.028) | (0.026) | (0.025) | (0.026) | (0.025) |
| | [0.004] | [0.002] | [0.002] | [0.002] | [0.011] | [0.011] | [0.004] | [0.014] |
| Achieved Level 5 | 0.025 | 0.028 | 0.028 | 0.028 | 0.023 | 0.022 | 0.024 | 0.022 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.011) | (0.010) | (0.011) | (0.011) |
| | [0.041] | [0.021] | [0.026] | [0.020] | [0.035] | [0.034] | [0.029] | [0.039] |
| Achieved Level 3 | -0.025 | -0.025 | -0.027 | -0.024 | -0.016 | -0.015 | -0.020 | -0.014 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.007) | (0.007) | (0.007) | (0.007) |
| | [0.003] | [0.002] | [0.001] | [0.002] | [0.024] | [0.033] | [0.005] | [0.046] |
| | **Panel B: Language scores** | | | | | | | |
| Test score | 0.082 | 0.085 | 0.091 | 0.087 | 0.087 | 0.086 | 0.092 | 0.087 |
| | (0.030) | (0.029) | (0.029) | (0.029) | (0.024) | (0.023) | (0.025) | (0.024) |
| | [0.006] | [0.003] | [0.002] | [0.003] | [0.000] | [0.000] | [0.000] | [0.000] |
| Achieved Level 5 | 0.035 | 0.037 | 0.040 | 0.038 | 0.036 | 0.036 | 0.037 | 0.036 |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.011) | (0.011) | (0.012) | (0.011) |
| | [0.012] | [0.007] | [0.004] | [0.006] | [0.002] | [0.001] | [0.001] | [0.001] |
| Achieved Level 3 | -0.022 | -0.022 | -0.024 | -0.022 | -0.023 | -0.023 | -0.025 | -0.022 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.006) | (0.006) | (0.006) |
| | [0.002] | [0.001] | [0.001] | [0.001] | [0.000] | [0.000] | [0.000] | [0.000] |
| Add LA-specific quadratic time trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Add School controls | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Exclude Top 5% programs | No | No | Yes | No | No | No | Yes | No |
| Exclude Top 1% programs | No | No | No | Yes | No | No | No | Yes |
| Observations | 142,366 | 142,366 | 132,408 | 138,634 | 179,797 | 179,797 | 165,868 | 174,930 |

**Note**. The table shows a number of robustness checks using the main IV specification considered in Table 9 for math (Panel A) and language (Panel B) scores. Columns (1) to (4) consider all students attending a school within 0.95km from a regeneration; columns (5) to (8) consider all students attending a school within 1.3km from a regeneration. Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), student scores at baseline (KS1), LA-specific time trends, and school, cohort, time, and child's block fixed effects. Columns (1) and (5) add LA-specific quadratic time trends; columns (2) and (6) add a vector of school composition controls for gender, ethnicity, subsidised lunch eligibility, special educational needs eligiblity, and regeneration movers; columns (3) and (7) exclude regeneration programs in the top 5% of the distribution of the number of housing units built; columns (4) and (8) exclude regeneration programs in the top 1% of the distribution of the number of housing units built. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

Table 11. Robustness checks: different control groups

| | Control group: all students attending a school between 1.3km and: | | | | | |
|---|---|---|---|---|---|---|
| | 1.7km | 1.8km | 1.9km | 2km | 2.1km | 2.2km |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A: Narrow sample** | | | | | |
| Math test scores | 0.062 | 0.072 | 0.085 | 0.077 | 0.071 | 0.086 |
| | (0.033) | (0.032) | (0.031) | (0.030) | (0.030) | (0.029) |
| | [0.064] | [0.025] | [0.006] | [0.011] | [0.019] | [0.003] |
| Language test scores | 0.061 | 0.071 | 0.087 | 0.075 | 0.073 | 0.080 |
| | (0.036) | (0.033) | (0.032) | (0.030) | (0.029) | (0.029) |
| | [0.095] | [0.029] | [0.006] | [0.013] | [0.014] | [0.006] |
| | **Panel B: Loose sample** | | | | | |
| Math test scores | 0.048 | 0.057 | 0.070 | 0.059 | 0.055 | 0.068 |
| | (0.031) | (0.029) | (0.027) | (0.026) | (0.026) | (0.025) |
| | [0.117] | [0.048] | [0.011] | [0.026] | [0.033] | [0.007] |
| Language test scores | 0.073 | 0.082 | 0.095 | 0.081 | 0.079 | 0.085 |
| | (0.032) | (0.027) | (0.026) | (0.025) | (0.024) | (0.023) |
| | [0.022] | [0.003] | [0.000] | [0.001] | [0.001] | [0.000] |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cohort FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Child's Block FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Baseline scores | Yes | Yes | Yes | Yes | Yes | Yes |
| LA-specific time trends | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 104,320 | 117,489 | 129,697 | 142,451 | 155,819 | 168,618 |

**Note**. The table shows 2SLS regressions of math and language test score on the occurrence of a regeneration program within 0.95km (Panel A) and 1.3km (Panel B). The same estimates using indicators for students awarded Level 3 and Level 5 for both subjects are available upon request. Every column uses a different control group, defined by all students attending a school within the distance stated in the header. Column (4) replicates the findings outlined in Table 9 (columns (3) and (6). Test scores in math and languaged are standardised by cohort to have zero mean and unit variance. All columns control for student characteristics (academy enrolment, gender, ethnicity, subsidised lunch eligibility, SEN eligibility, regeneration mover, distance to school, distance to regeneration), student scores at baseline (KS1), LA-specific time trends, and school, cohort, time, and child's block fixed effects. Standard errors, shown in brackets, are clustered on schools. P-values are shown in square brackets.

## Table 12. Effects of regeneration programs on school outcomes

| | Sample: | | | | | |
|---|---|---|---|---|---|---|
| | Narrow | | | Loose | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel B. Funding** | | | | | |
| Total funds | 0.093 | 0.061 | 0.053 | 0.122 | 0.045 | 0.042 |
| | (0.119) | (0.045) | (0.043) | (0.110) | (0.040) | (0.040) |
| | [0.433] | [0.175] | [0.216] | [0.270] | [0.265] | [0.289] |
| Staffing funds | 0.073 | 0.005 | -0.005 | 0.091 | -0.025 | -0.030 |
| | (0.121) | (0.046) | (0.042) | (0.113) | (0.042) | (0.039) |
| | [0.544] | [0.919] | [0.907] | [0.419] | [0.544] | [0.449] |
| Funds for learning resources | 0.071 | -0.081 | -0.084 | 0.113 | -0.094 | -0.092 |
| | (0.114) | (0.073) | (0.070) | (0.106) | (0.070) | (0.068) |
| | [0.536] | [0.270] | [0.231] | [0.289] | [0.178] | [0.174] |
| | **Panel A. Teachers** | | | | | |
| Percent qualified teachers | -0.107 | 0.092 | 0.091 | -0.168 | 0.049 | 0.044 |
| | (0.092) | (0.118) | (0.119) | (0.086) | (0.109) | (0.108) |
| | [0.242] | [0.435] | [0.444] | [0.052] | [0.656] | [0.682] |
| School pupil-to-teacher ratio | -0.118 | 0.021 | 0.014 | -0.129 | 0.016 | 0.021 |
| | (0.090) | (0.110) | (0.109) | (0.081) | (0.098) | (0.097) |
| | [0.190] | [0.849] | [0.896] | [0.111] | [0.867] | [0.828] |
| School FE | No | Yes | Yes | No | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | No | Yes | No | No | Yes |
| Observations | 2,672 | 2,672 | 2,672 | 3,733 | 3,733 | 3,733 |

**Note**. This table shows the effects of regeneration programs on number of school outcomes related to staffing (Panel A) and funding (Panel B). Outcomes are standardised to have zero mean and unit variance. Columns (1) to (3) consider results for the sample including all schools located within the average student's home-school distance; columns (4) to (6) consider all schools located within the 80th percentile of the student's home-school distance distribution. Total funds include all funds assigned from the Local Authority to the school; staffing funds include funds used for teachers and other educational support staff; funds for learning resources include ICT, development and training, and other resources (e.g. textbooks). All columns control for year and time fixed effects; columns (2) and (5) add school fixed effects; columns (3) and (6) add controls for school composition (percent native, white, black, asian, male, students eligible for subsidised lunches, students with SEN, average KS1 score) and enrolment. Standard errors, shown in brackets, are clustered on postcodes. P-values are shown in square brackets.

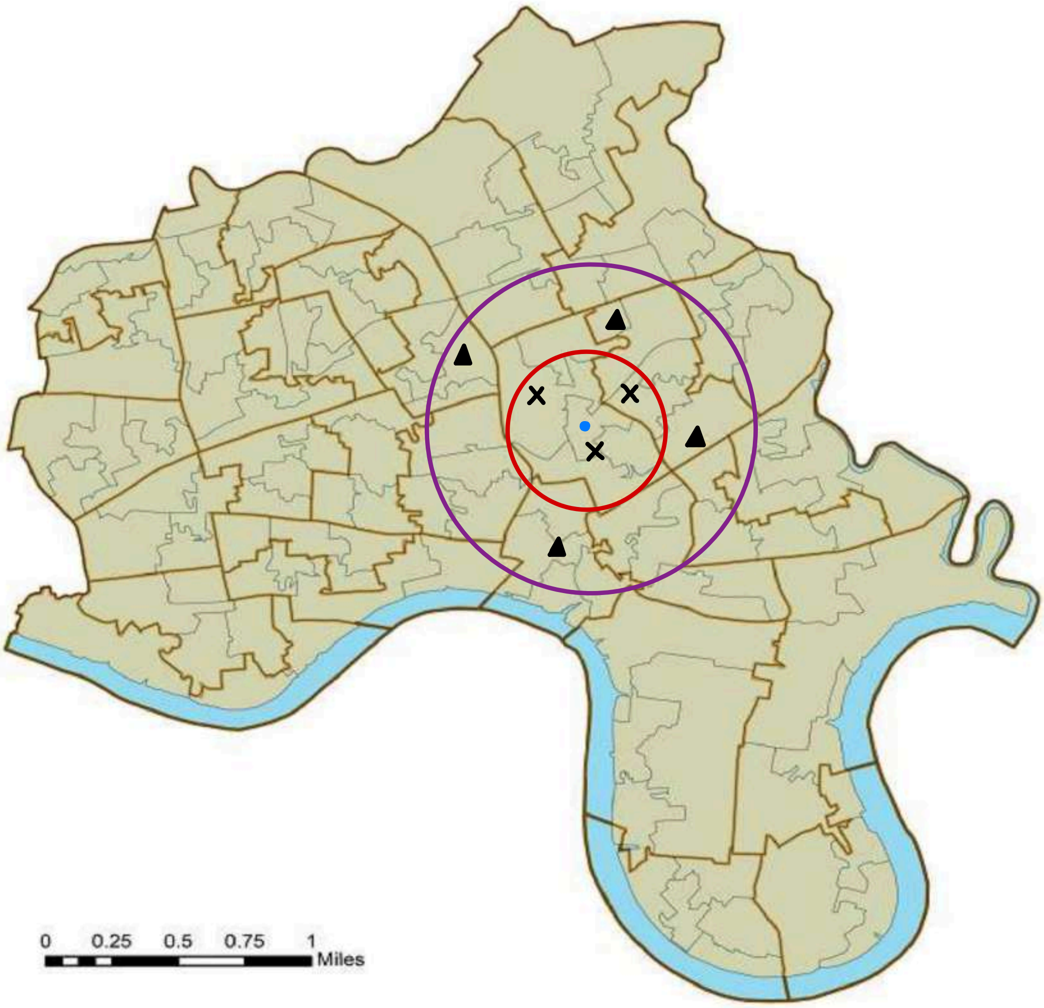
Figure 1. The regeneration of the Meredith Tower in West London

Panel A. Existing building

Panel B. New building

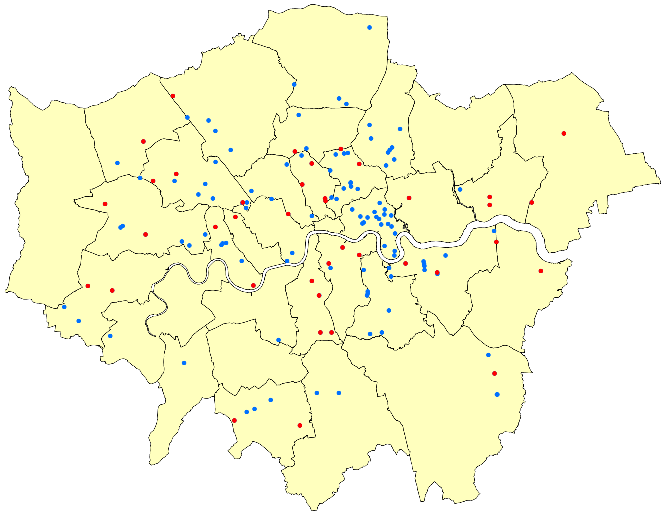
**Note**. This figure shows an example of a regeneration program carried out in West London. Panel A shows the building slated for demolition; Panel B shows a digital rendering of the new building constructed on site.

Figure 2. Graphical visualisation of DID strategy

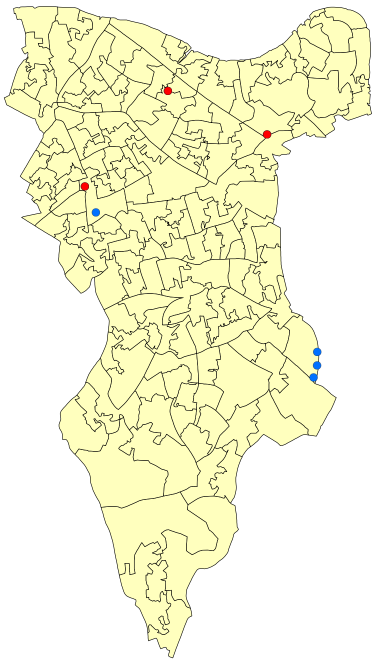



**Note**. This figure shows an example of the DID strategy outlined in Section 3 for the loose sample. The figure shows the map of Tower Hamlets, a council located in the East End of London, comprising 130 blocks (grey outline). The Blue dot represents a regeneration program. All students attending schools located within 1.3km are included in the treatment group (red outline), whereas all students attending schools located between 1.3 and 2km are included in the control group (purple outline).

Figure 3. Maps of regeneration programs



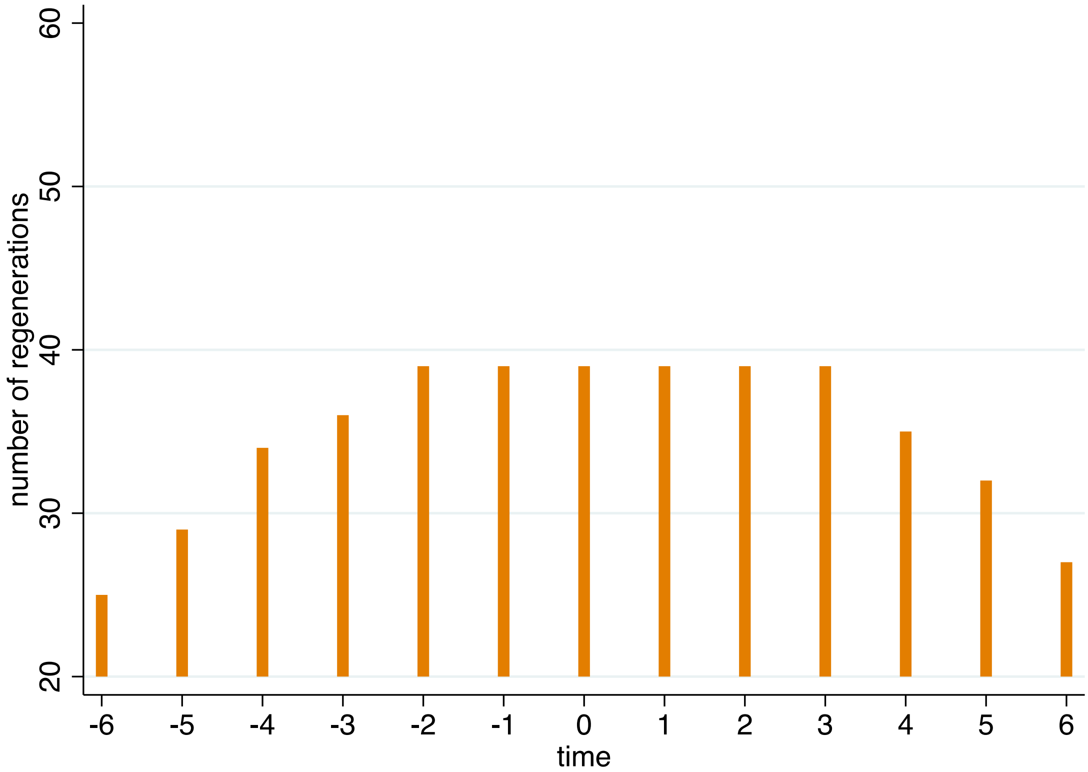
Panel A. Greater London



Panel B. Southwark

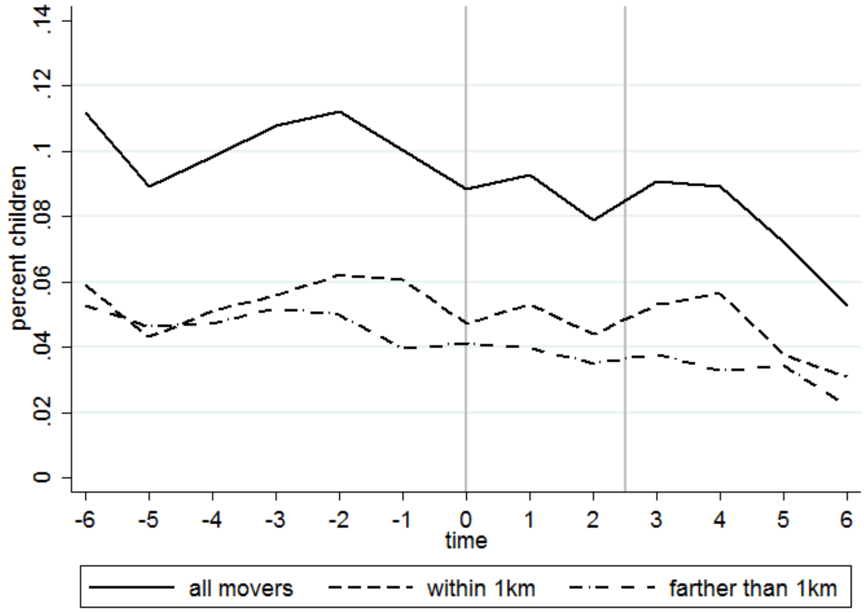
**Note**. This figure plots all regeneration programs completed between 2006 and 2016 in Greater London (Panel A) and one of London's local councils (Southwark, Panel B). The 33 London local councils are marked by the black outline in Panel A. Census blocks (LSOAs) are marked by the black outline in Panel B. Regenerations included in the final sample are marked with red dots.

Figure 4. Number of regeneration programs by time

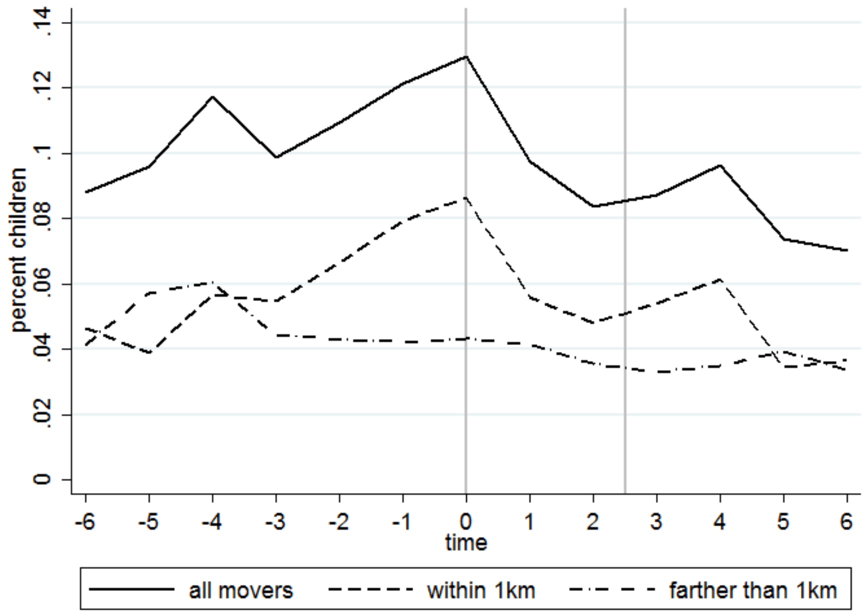



**Note**. The figure shows the number of regeneration programs at every point in time. The time of the demolition is set to 0, whereas the end of the construction is set 2 years after the demolition.

Figure 5. Children living on the regenerated premises



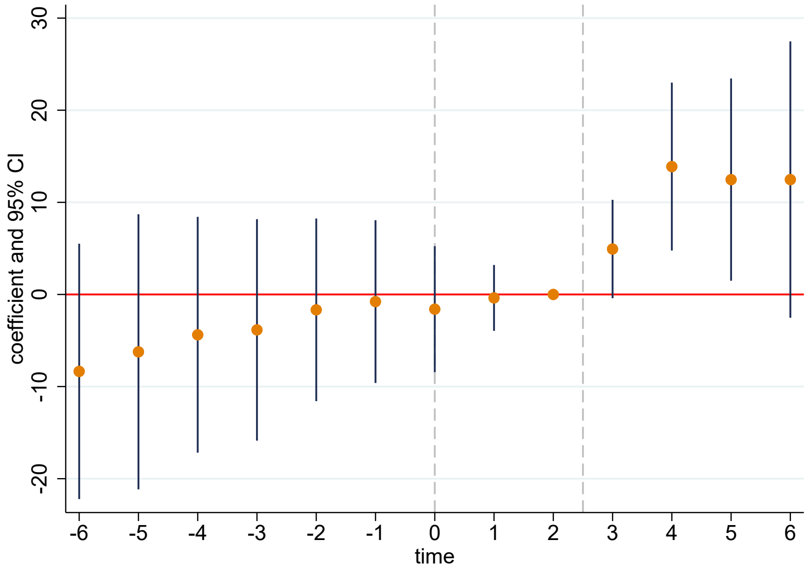

Panel A. Small developments



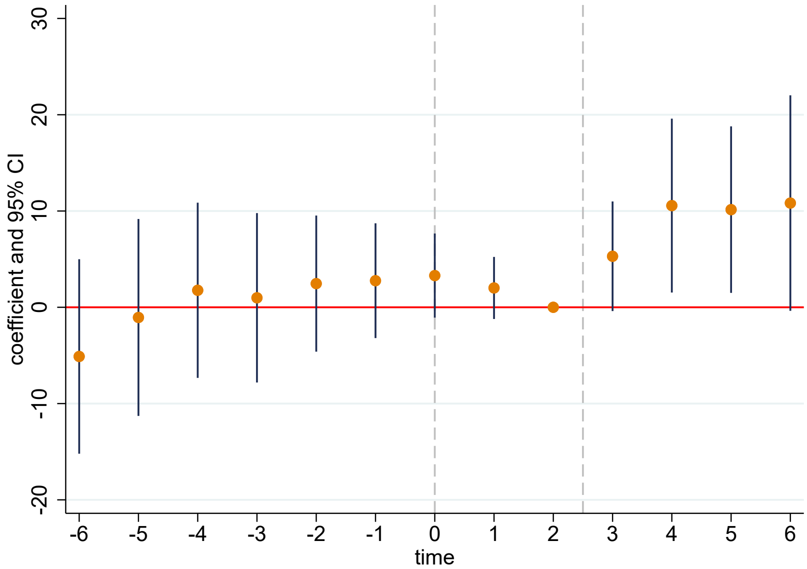

Panel B. Big developments

**Note**. The figure shows the fraction of children leaving a block with a regeneration starting at time 0 considering regeneration programs involving buildings with less than 117 housing units (Panel A) and buildings with more than 117 housing units (Panel B). 117 units is the average number of units within the new building among all regenerations programs providing at least for 10 new housing units. The solid line considers all children moving out at a given time; the dash line considers children moving out of the block and relocating within 1km from the regeneration; the dash-dotted line considers children moving out and relocating farther than 1km.

Figure 6. Number of children before and after




Panel A. All children

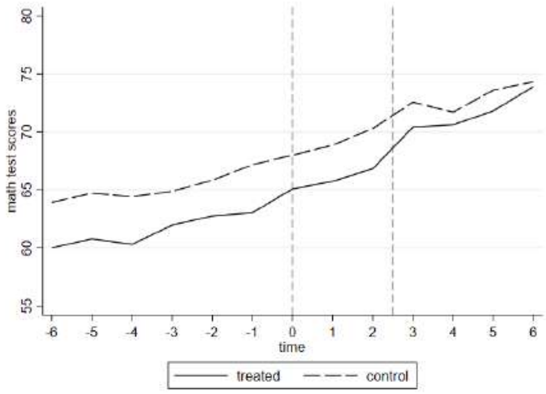



Panel B. Children not eligible for subsidised lunches

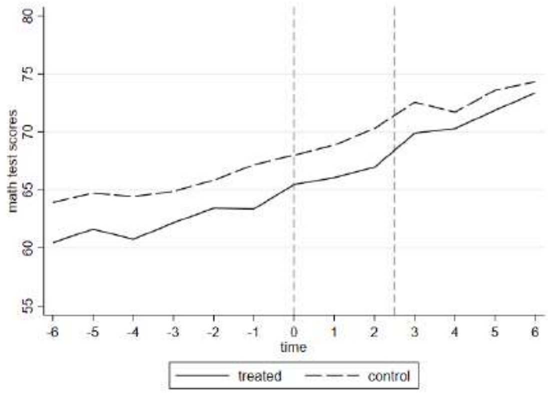
**Note**. This figure shows the number of children (Panel A) and the number of children not receiving subisidised lunches (Panel B) living on the regeneration's site before and after the end of the program. The time of the demolition is set to 0, whereas the end of the construction is set between 2 to 3 years after the demolition. Each Panel plots coefficients (orange dots) and 95% confidence interval (vertical spikes) obtained from a DID specification similar to equation (3) estimated at block level. The control group is represented by all blocks located 2km from a regeneration.

Figure 7. Pre trends for student test scores

A. Math test score

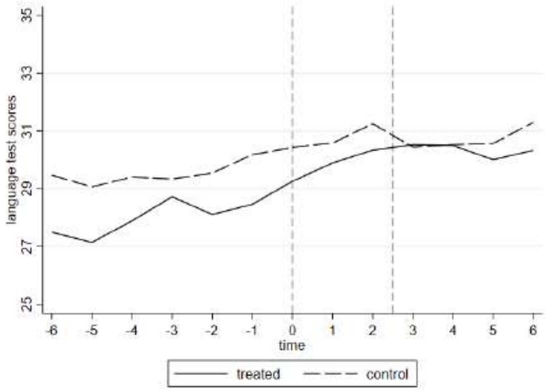



Panel 1. Narrow sample

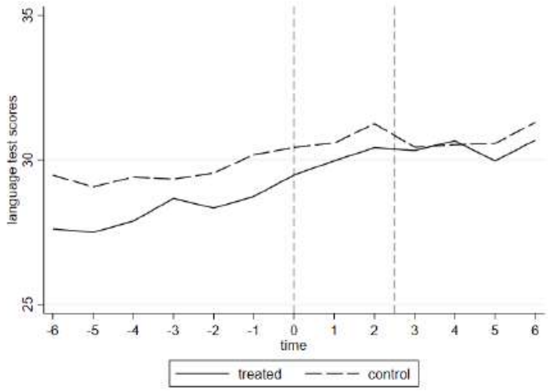



Panel 2. Loose sample

B. Language test scores



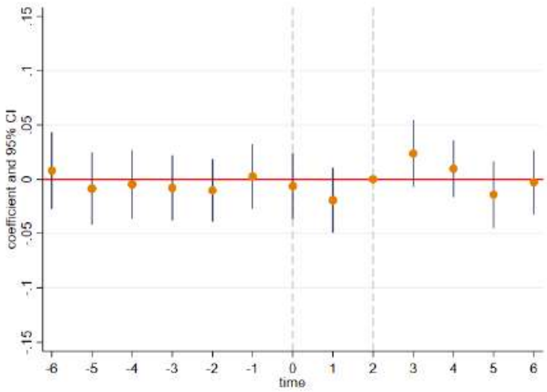

Panel 1. Narrow sample



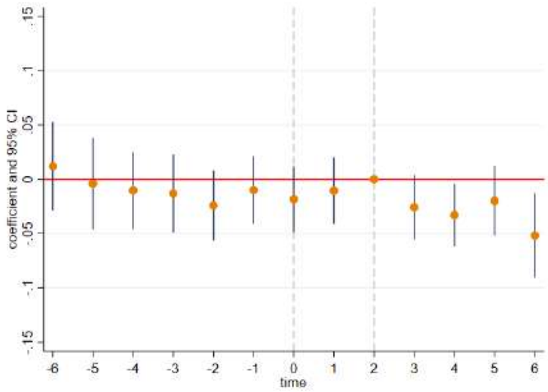

Panel 2. Loose sample

**Note**. The figure shows pre-trends for treated (solid line) and control (dashed line) student test scores at the end of primary school for math (panels A1 and A2) and language (panels B1 and B2). Panels A1 and B1 consider the narrow sample; panels A2 and B2 consider the loose sample. The time of the demolition is set to 0, whereas the end of the construction is set between 2 to 3 years after the demolition.

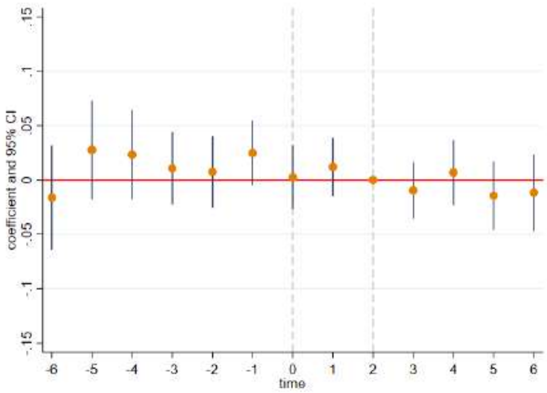
Figure 8. School Composition



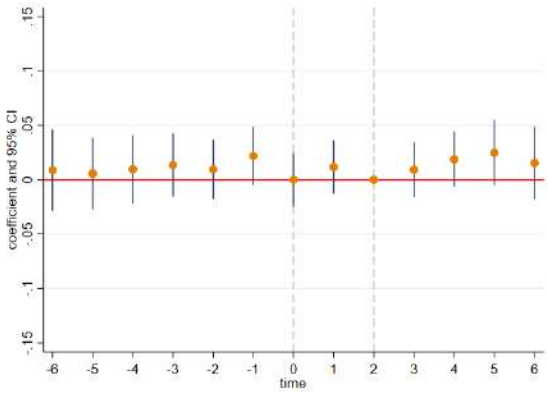

Panel A. Percent males



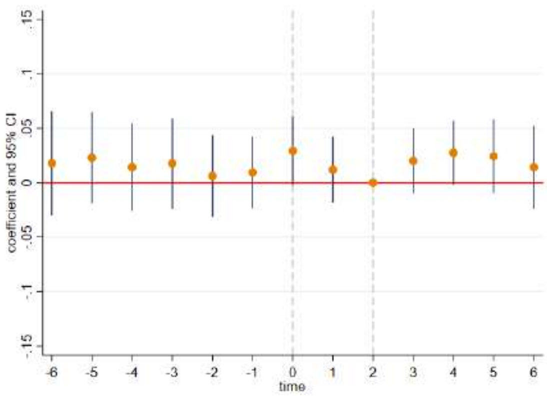

Panel B. Percent on subsidised lunch



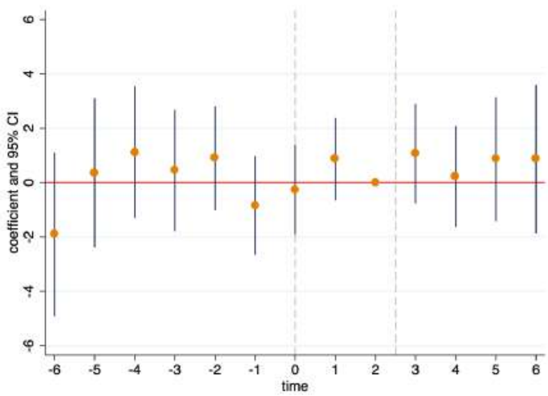

Panel C. Percent natives




Panel D. Percent blacks



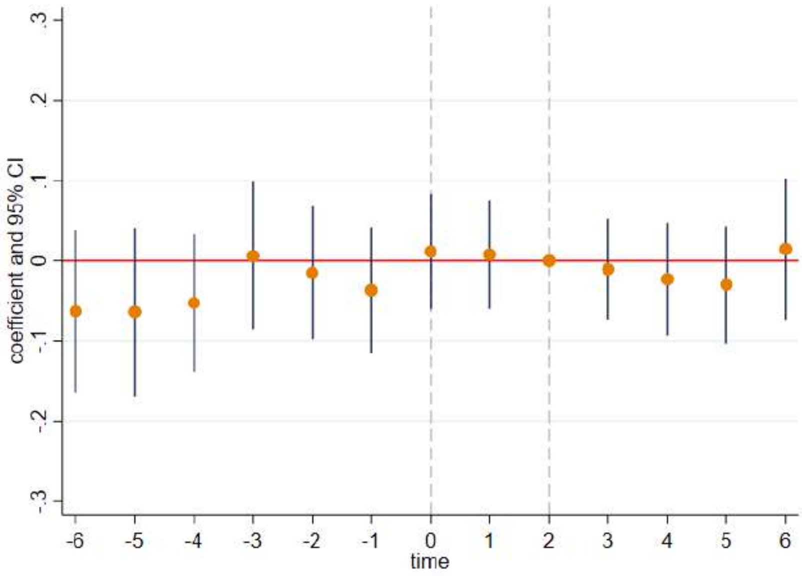

Panel E. Percent with SEN



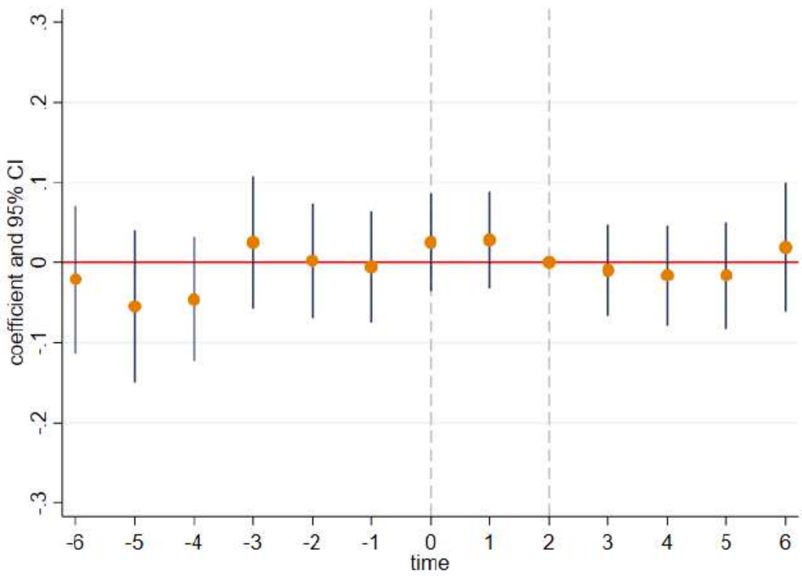

Panel F. School enrolment

**Note**. The figure shows differences in school characteristics between treated and control schools over time for percent males (Panel A), eligible for subsidised lunches (Panel B), natives (Panel C), black students (Panel D), students with SEN (Panel E), and school enrolment (Panel F). The time of the demolition is set to 0, whereas the end of the construction is set between 2 to 3 years after the demolition. Each panel plots the point estimates (orange dots) and their 95% confidence interval (vertical spikes) obtained from a school-level version of equation (3) controlling for time, cohort and school fixed effects, and LA-specific time trends. Only the narrow sample is considered; estimates for the loose sample are similar and can be found in the Appendix.

Figure 9. Student baseline scores




Panel A. Narrow sample

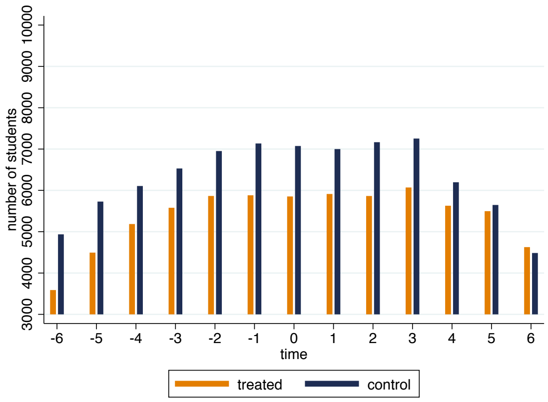



Panel B. Loose sample

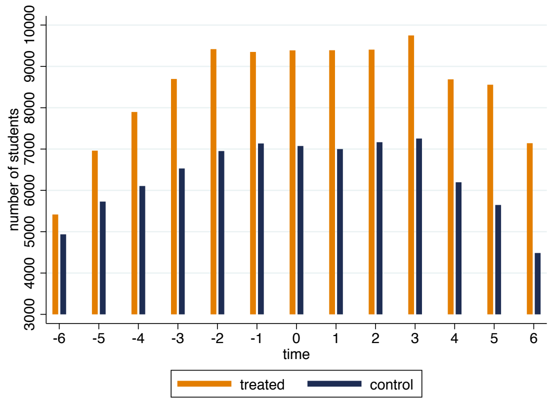
**Note**. The figure shows differences in baseline scores (KS1 standardised Average Point Score) between treated and control schools over time for the narrow sample (Panel A) and the loose sample (Panel B). The Average Point Score is a pseudo-continuous measure obtained assigning every student a number of points (from 3 to 33) according to the Level awarded in every subject (math, language, science) and then taking the average. The time of the demolition is set to 0, whereas the end of the construction is set between 2 to 3 years after the demolition. Each panel plots the point estimates (orange dots) and their 95% confidence interval (vertical spikes) obtained from a school-level version of equation (3) controlling for time, cohort and school fixed effects, and LA-specific time trends. Estimates using the Level awarded in every single subject are similar and available upon request.

Figure 10. Student and school distribution over time

A. Students

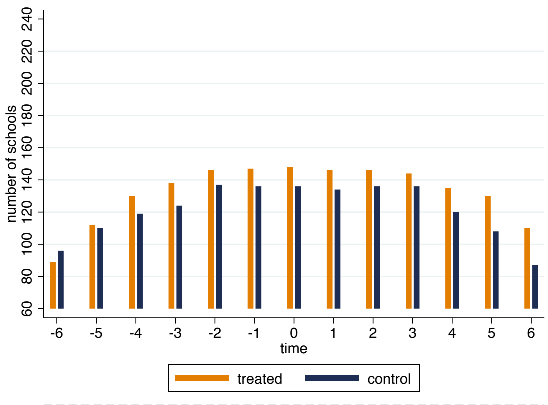



Panel 1. Narrow sample

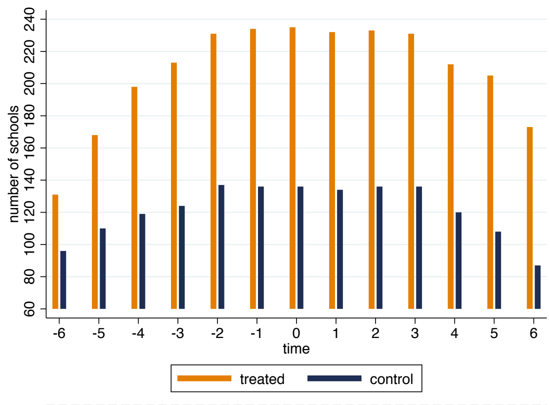



Panel 2. Loose sample

B. Schools




Panel 1. Narrow sample

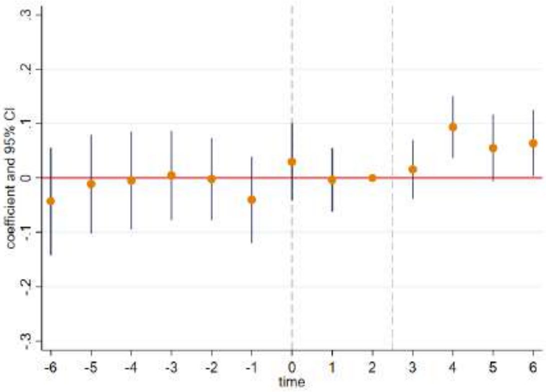



Panel 2. Loose sample

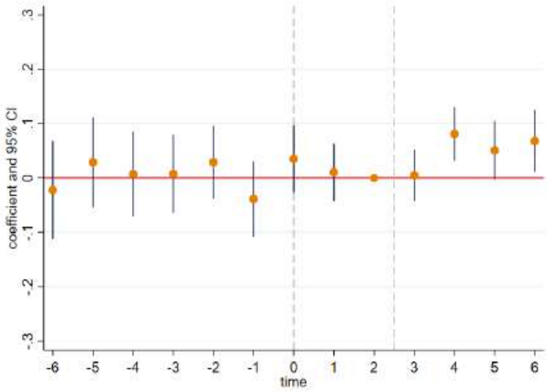
**Note**. The figure shows the distribution of students (panels A1 and A2) and schools (panels B1 and B2) over time in the treated and control group (orange and blue bars respectively). Panels A1 and B1 plot the distributions for the narrow sample, whereas panels A2 and B2 for the loose sample.

Figure 11. Event studies for math and language

A. Math scores

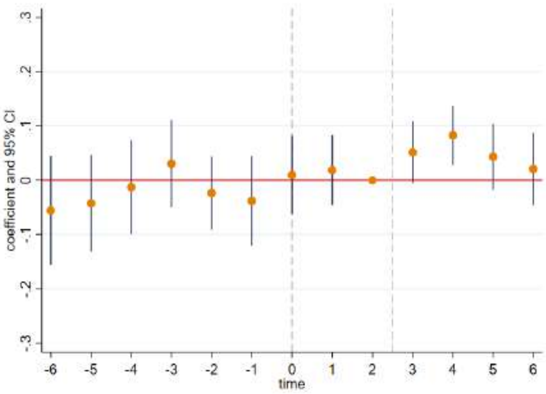



Panel 1. Narrow sample

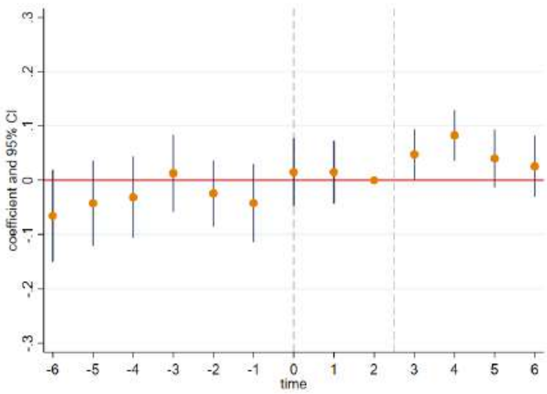



Panel 2. Large sample

B. Language scores



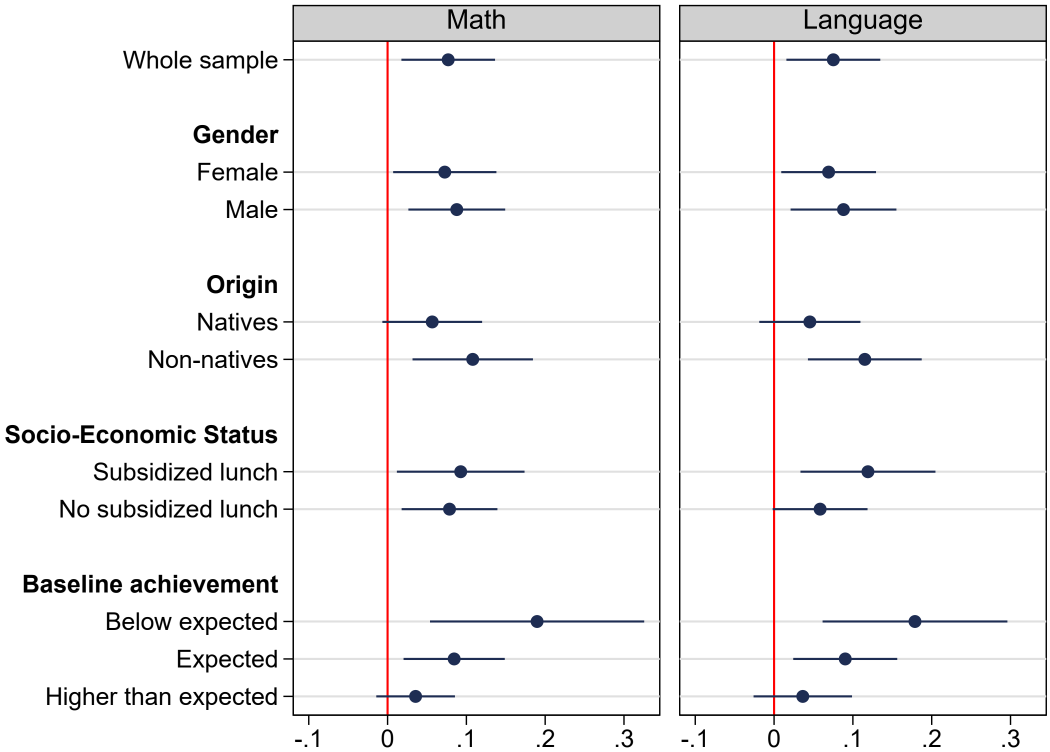

Panel 1. Narrow sample




Panel 2. Large sample

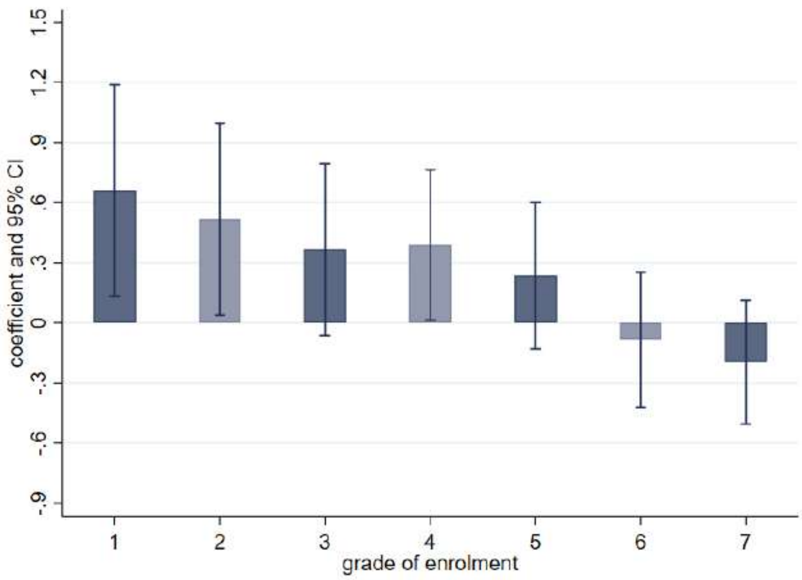
**Note**. The figure shows event study estimates for math scores (panels A1 and A2) and language scores (panels B1 and B2). The time of the demolition is set to 0. The reference time is set to 2, right before the expected end of the regeneration program. Estimates are obtained adding leads and lags to equation (4). Leads are obtained interacting the treatment dummy with time-specific effects; lags are obtained interacting the grandfathering eligibility indicator with time-specific effects. Each Panel shows the point estimate (orange dot) and its 95% confidence interval.

Figure 12. Heterogeneous effects

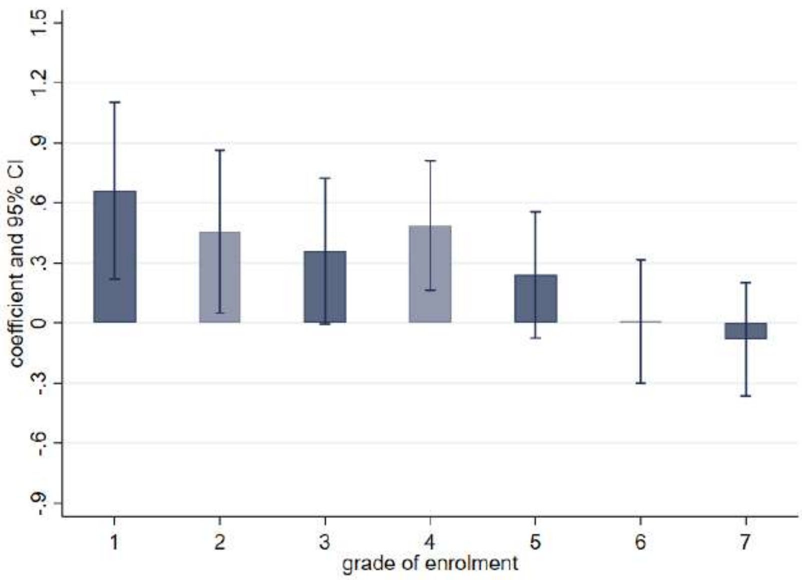



**Note**. This figures shows heterogeneous effects of the treatment obtained by estimating equation (3) instrumenting $D \cdot T$ with $G \cdot T$ and stratifying the sample by student characteristics (gender, socio-economic status, origin, and baseline achievement at KS1). The left-hand panel shows the results for math test scores, whereas the right-hand panel for language test scores. Each panel plots the point estimate and its 95% confidence interval (horizontal spikes). Only estimates for the narrow sample are considered; estimates for the loose sample are similar and can be found in the appendix.

Figure 13. Enrolment by grade of affluent children




Panel A. Narrow sample

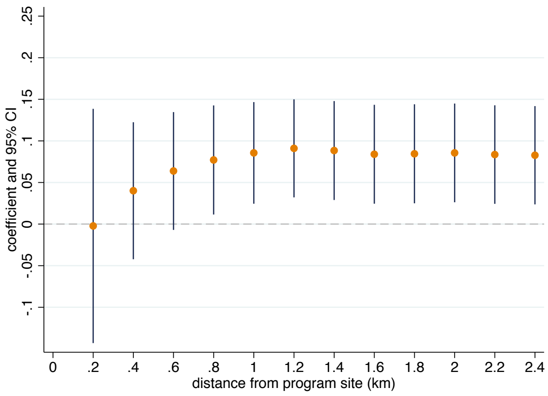



Panel B. Loose sample

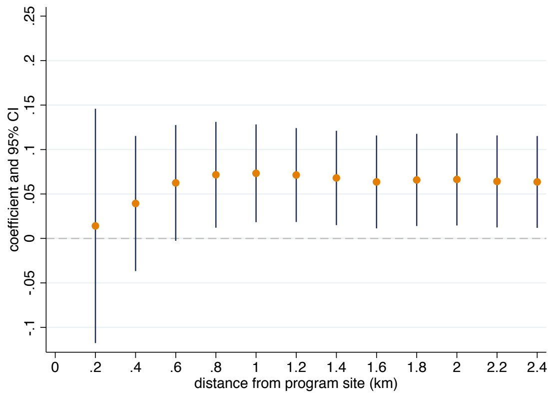
**Note**. The figure shows DID estimates of the number of affluent children living on the regeneration site and enrolled in local schools located within 0.95km (Panel A) and within 1.3km (Panel B) from a regeneration, by grade of enrolment. Bars show the DID coefficients and the vertical spikes indicate 95% confidence intervals. The latter are obtained from a DID specification similar to equation (3) estimated at school level and controlling for cohort, time, and school fixed effects. More affluent children are defined as those not eligible for subsidised lunch at school. Local schools are those located within 0.95km from a regeneration. Results considering schools located within 1.3km are available upon request.

Figure 14. Effect of regeneration by distance to student residence

A. Math scores

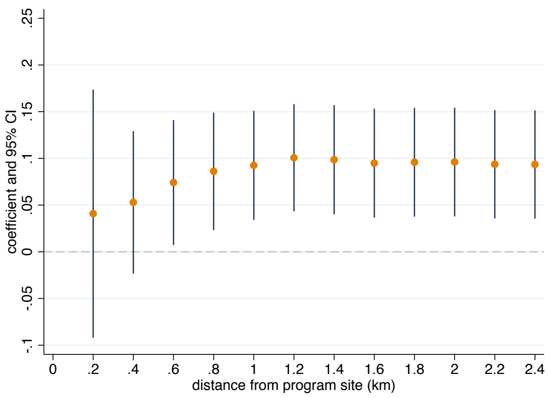



Panel 1. Narrow sample

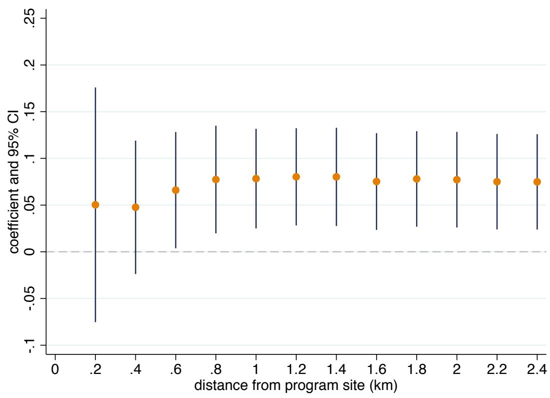



Panel 2. Loose sample

B. Language scores



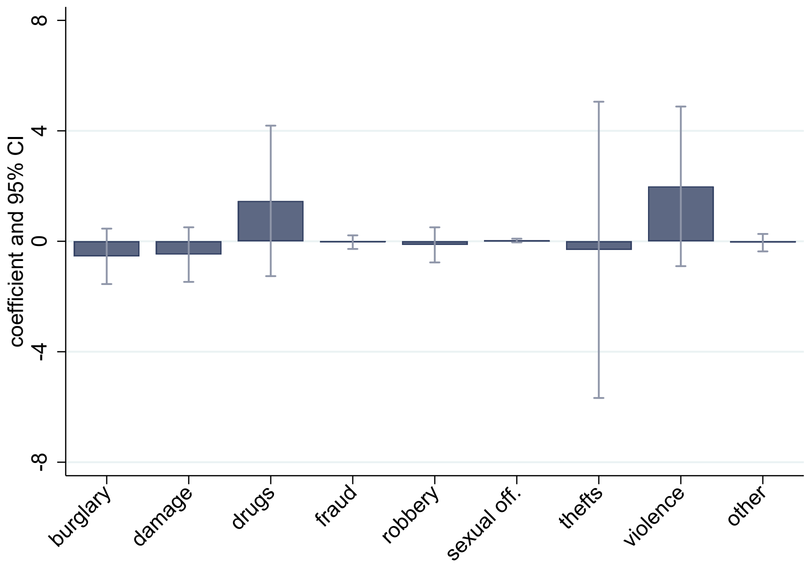

Panel 1. Narrow sample



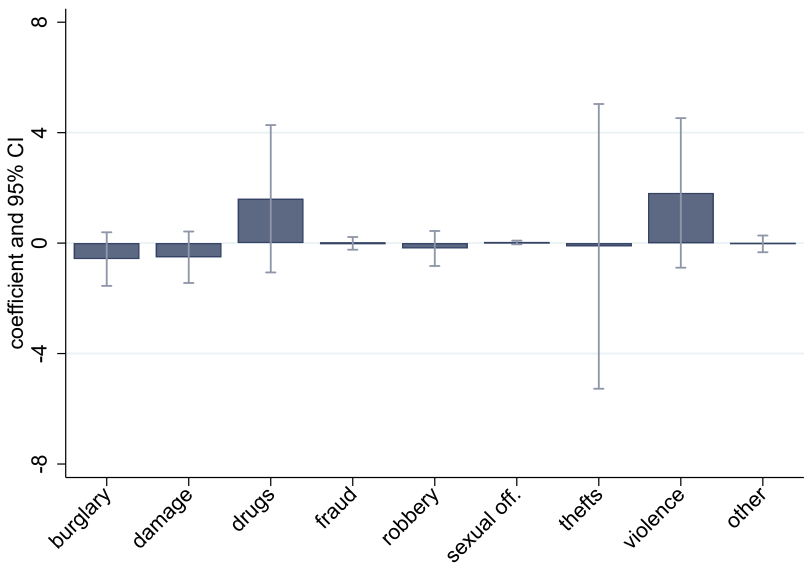

Panel 2. Loose sample

**Note**. The figure shows 2SLS effects of the treatment obtained by estimating equation (3), instrumenting $D \cdot T$ with $G \cdot T$, and considering students living at different distances from the regeneration. Panel A1 and A2 show the results for math; panels B1 and B2 show the results for language. Each Panel shows the point estimate (orange dot) and its 95% confidence interval.

Figure 15. Number of criminal offences around the regeneration site




Panel A. Narrow sample

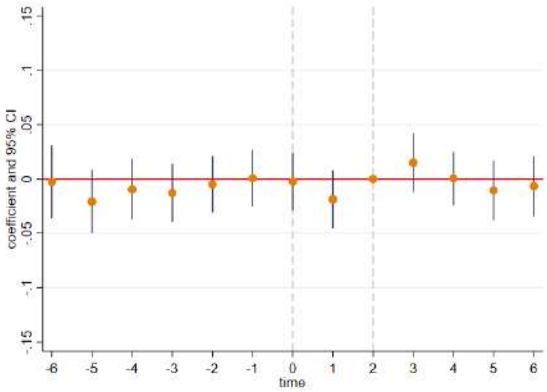



Panel B. Loose sample

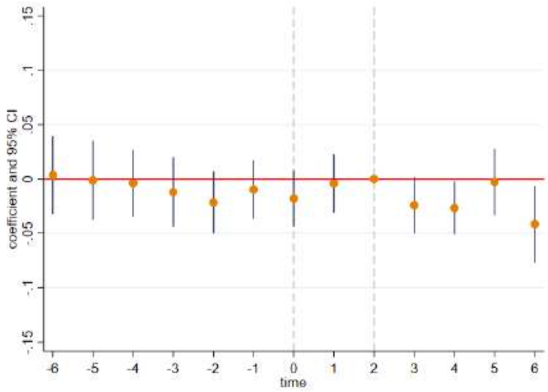
**Note**. The figure shows DID estimates of the number of criminal offences committed within 0.95km (Panel A) and within 1.3km (Panel B) from a regeneration. Bars show the DID coefficients and the vertical spikes indicate 95% confidence intervals. The latter are obtained from a DID specification similar to equation (3) estimated at block (LSOA) level and controlling for year, time, and block fixed effects.

# Appendix A. Additional Estimates for Loose Sample

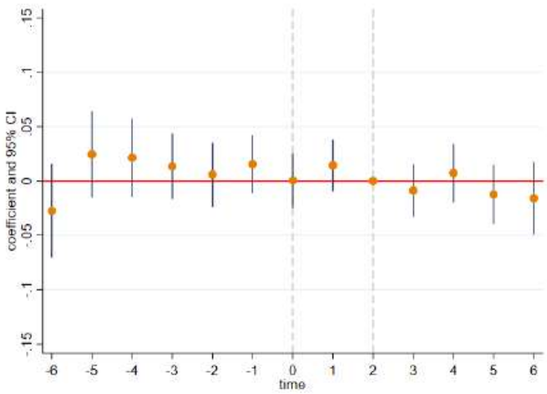
Figure A1. School Composition (loose sample)



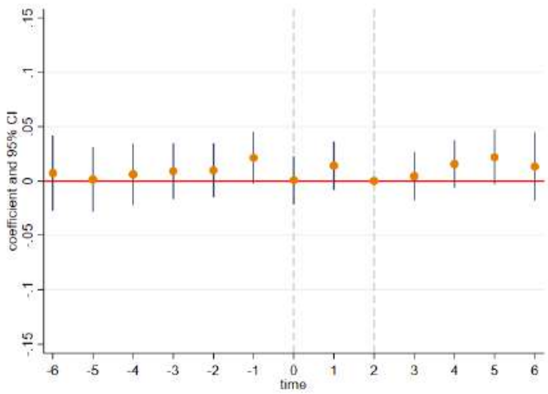

Panel A. Percent males



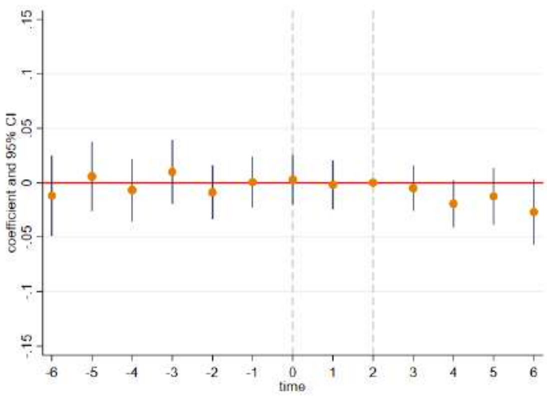

Panel B. Percent on subsidised lunch



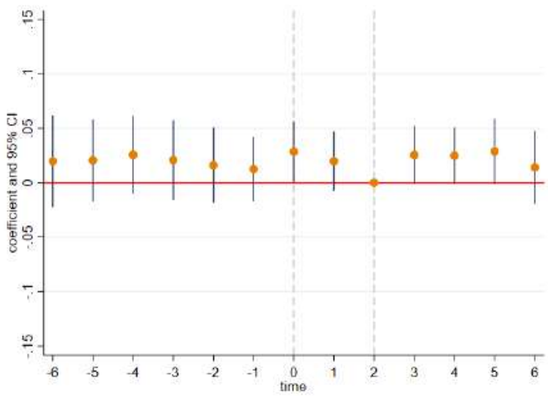

Panel C. Percent natives




Panel D. Percent blacks



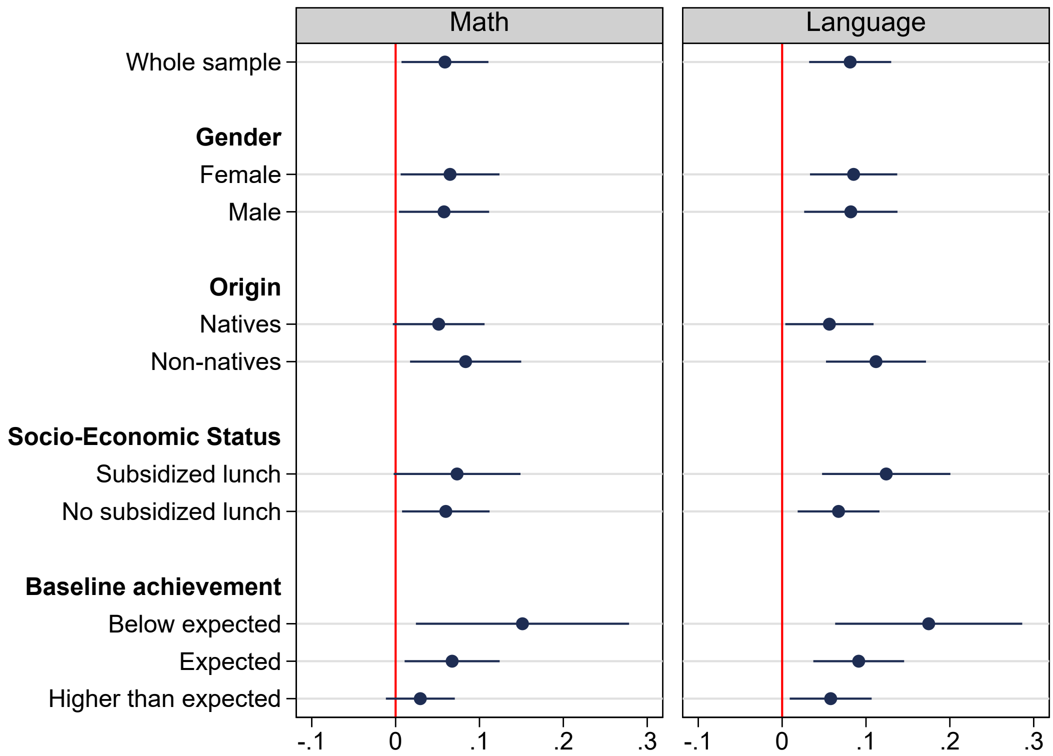

Panel E. Percent whites




Panel F. Percent with SEN

**Note**. The figure shows differences in school characteristics between treated and control schools over time for percent males (Panel A), eligible for subsidised lunches (Panel B), natives (Panel C), black students (Panel D), students with SEN (Panel E), and school enrolment (Panel F). The time of the demolition is set to 0, whereas the end of the construction is set between 2 to 3 years after the demolition. Each panel plots the point estimates (orange dots) and their 95% confidence interval (vertical spikes) obtained from a school-level version of equation (3) controlling for time, cohort and school fixed effects, and LA-specific time trends. Only the loose sample is considered.

Figure A2. Heterogeneous effects (loose sample)




**Note**. This figures shows heterogeneous effects of the treatment obtained by estimating equation (3) instrumenting $D \cdot T$ with $G \cdot T$ and stratifying the sample by student characteristics (gender, socio-economic status, origin, and baseline achievement at KS1). The left-hand panel shows the results for math test scores, whereas the right-hand panel for language test scores. Each panel plots the point estimate and its 95% confidence interval (horizontal spikes). Only estimates for the loose sample are considered.

School of Economics and Finance

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