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Abstract

Education in Denmark is freely available. Despite near equal teacher salaries and per-pupil school expenditure across districts, there is substantial spatial heterogeneity in school quality as measured by teacher quality and student test scores. We argue that this is due to sorting of teachers and students across neighborhoods. We develop and apply multiple methods for identifying parental evaluations of measured school quality in the presence of strong neighborhood sorting. There is strong concordance in the estimates across diverse methodologies. We estimate a willingness to pay of about 3% more for a house with average characteristics when test scores are one standard deviation above the mean. Controlling for selection into neighborhoods only slightly reduces our estimates. Given that school quality, as measured by monetary resources, is equalized across all neighborhoods, payments for school quality embodied in housing prices are in fact payments for peer, teacher, and neighborhood quality. This evidence challenges the appropriateness of the current emphasis in the literature on Tiebout-based models of neighborhood choice that stress sorting on parental income in order to finance the local public good of school quality. Rather, a model of neighborhood choice to select neighbor and peer quality is more appropriate. Our evidence is consistent with evidence that cash expenditures on classrooms have weak effects on child achievement.

JEL Codes: H0, H4, H7, I2, R0, R2, R3

Keywords: hedonic valuation, amenities, residential sorting, peer effects.

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1 Introduction

The Scandinavian welfare state is widely regarded as an exemplary system that reduces inequalities and equalizes opportunities by providing an education system that is free for all and that equalizes per-pupil expenditures across schools. Yet, there is growing evidence that such equalization, enshrined in the law, is undone in practice through the sorting of households and teachers across neighborhoods (Eshaghnia, 2021; Gensowski et al., 2021; Heckman and Landersø, 2022).

This paper estimates parental preferences for schools with high-quality peers and teachers in a setting where per-pupil school expenditures are virtually equal. To do so, we develop and apply a variety of approaches using Danish register data in a context with strong neighborhood sorting.

We make several contributions to the literature. Sorting on the basis of preferences and income to produce local public goods has been studied since Tiebout (1956). Bénabou (1993, 1996), Durlauf (1996), and Durlauf and Seshadri (2018) analyze how neighborhood sorting affects child development through peer effects and provision of schooling quality. Epple et al. (2020) and Sieg (2020) summarize the local public goods literature on the provision of schooling. This literature focuses on the tax and spending decisions of agents living in neighborhoods and their impact on schooling expenditure.

The mechanism of unequal spending by districts is often discussed in explaining inequality in child outcomes across districts,[1] but in Denmark it is absent. Per-pupil expenditures and teacher salaries are mandated to be equal across public schools except for students with special needs and for cost-of-living adjustments. Tiebout sorting to raise revenue for financing school quality is absent, although sorting still occurs. High-quality teachers are attracted to schools with high-quality students and parents. This non-monetary allocation mechanism is at work despite the inability of districts to determine salaries or their need to finance local public goods.

Flyer and Rosen (1997) discuss a similar mechanism. Differences in school quality are not driven by differences in schooling expenditure, but by the sorting of parents,

[1] See, for instance, Jackson et al. (2016), Hyman (2017), and Lafortune et al. (2018).

teachers, and students. Our analysis explains the recurrent findings in the literature on educational finance that "money doesn't matter" (see Coleman (1966) and Hanushek (1997)). Basic forces promoting sorting of peers and parents are at work. A companion paper, Eshaghnia et al. (2023), shows the strong effects of this sorting on a number of later life outcomes, including income and educational attainment.

This paper estimates how much parents value peer and teacher quality in terms of their willingness to pay (WTP) for houses with identical attributes. By estimating parental demand for neighborhood and teacher quality, this paper investigates a possible mechanism behind notable inequities in intergenerational social mobility in Denmark (Eshaghnia et al., 2022; Landersø and Heckman, 2017), despite its strongly egalitarian state policy. Money only goes so far. Parents and peers play powerful roles.

We use a variety of approaches summarized in Table 1 to reach these conclusions. One strength of this paper is the concordance of the estimates from very different approaches used in the spirit of Kuznets (see, e.g., Fogel, 1987). No single assumption or methodology drives our results.

Table 1: Summary of the Strategies Employed to Identify the WTP for Measured School Quality

	Method Description	Identifying Assumptions
(1)	**Hedonic regressions:** Neighborhood fixed-effect model with neighborhood and housing attributes as controls (fixed-effects at varying levels of geographical granularity).	(i) Regressors control for sorting across school boundaries, within large, and small cluster level (Sections 6 and 6.4.1); and (ii) school quality differences are captured by average test scores.
(2)	**Mixed continuous-discrete neighborhood choice model:** Outcomes controlling for selection into neighborhoods and schools.	(i) and (ii) as in (1); (iii) Distance to grandparents enters in household's utility for neighborhoods but does not influence house prices.
(3)	**Capitalization effect:** Exploiting variation in school boundaries and resulting variation in school quality.	School boundary changes are exogenous to enrollment decisions.
(4)	**Alternative data:** Using transaction prices instead of government valuation of house values.	As in (1). Measurement error in the dependent variable is diminished.
(5)	**Bounding the impact of unobservables:** Applying Altonji et al. (2005); Diegert et al. (2022); Oster (2019) to bound the impact of omitted variable bias.	Plausible magnitudes of the importance of unobservables.

This paper unfolds in the following way. We first describe our rich administrative data covering the full Danish population. We then examine small geographic units of neighborhoods, with a median area of 0.34 square miles, and show strong sorting within narrowly defined clusters.

We know individual residential street addresses. For each housing unit, we know numerous attributes including assigned school catchment areas, types of buildings, the number of floors, the number of units per building, the number of bedrooms, toilets, and bathrooms, the size of the living area, and the age of the property. Following the received literature, our measure of school quality is average student grades at the school level.[2] Using variation within narrow geographic clusters, we study parental willingness to pay for school quality, including peers and teacher quality, by controlling for characteristics that predict housing prices. Cluster indicators are used to control for unobserved neighborhood attributes in a fashion similar to Bayer et al. (2007).

Controlling for housing and neighborhood characteristics, households are willing to pay 2% to 3.5% more for housing for a one–standard deviation increase in school quality. Our preferred estimate of 2.7% implies that households are willing to pay about $6,700 for a one–standard deviation increase in average test scores for a house with mean attributes. This is broadly in line with estimates reported for other countries with greater inequality in income and wealth than Denmark, including Australia, France, the UK, and the US.[3] This paper applies and improves on methods used to identify and estimate the marginal willingness to pay for measured school quality by using a variety of different approaches to reach the same conclusion. It also gives our estimate a different interpretation, given the equalization of per-pupil school expenditure in Denmark. Households are paying to attend schools with better student, peers, and teachers, and with better adult peers.[4] Our results are robust to use of alternative

[2]See, e.g., Avery and Pathak (2021); Bayer et al. (2007); Black (1999); Epple and Romano (2003).

[3]See, e.g., Bayer et al. (2007); Black (1999); Fack and Grenet (2010); Gibbons and Machin (2003); Gibbons et al. (2013) and Black and Machin (2011), for a review.

[4]Our findings are consistent with results in the literature studying parental preferences and school choice policies in the US, e.g. Abdulkadiroğlu et al. (2020); Agostinelli et al. (2021); Rothstein (2006). These studies emphasize the central role played by parental preferences for peers, which limits demand-side pressure for improving school productivity.

approaches for controlling selection into neighborhoods.

One byproduct of our analysis is that multiple possible measures of school quality – average test scores, peer quality, teacher quality, value-added – are strongly intercorrelated with each other. A literature that focuses on average test scores misses these other dimensions of parental demand for quality. Given that our estimates of parental willingness to pay for average test scores are in accord with those in the received literature based on samples with wide variation in per-pupil expenditure, we eliminate one possible candidate interpretation of the sources of variation in school quality.

2 The Public Schooling System in Denmark

The Danish schooling system is based on the principle of equal expenditure on schooling per-pupil for all, which is provided at no charge in public schools through the university level. Specifically, per-pupil expenditure is equalized in Denmark through a system of redistribution across municipalities but not necessarily other dimensions of school quality. To achieve this, redistribution is needed since primary sources of municipality revenue (about 70%) is collected from local taxes. Despite the tax rate varying only minimally across municipalities (OECD, 2016), tax bases do vary, which motivates a redistributive system across municipalities.[5]

Figure 1 display the distributions of total expenditures across municipalities. The Danish distributions are much more concentrated than those for the US. Dalsgaard and Andersen (2016) show that more than 50% of the heterogeneity in schooling expenditure across municipalities is due to compensatory finance that accounts for factors, such as the fraction of non-westerners across municipalities.

Despite near equalization in school expenditure and teacher salary distributions, teachers still sort based on the quality of the students they are teaching. Differences

[5]Residual differences in funding across municipalities is small after controlling for a number of municipality features (share of private school students, share of immigrants (to proxy special needs and language expenses), distance to school (rural areas have less possibility of economies of scale), specific housing types, population size (to approximate returns to scale), trend in the numbers of school age children (budgets tend to respond to lagged changes in the number of students)). The residual is not correlated with factors such as voting behavior.

in school quality are not driven by differences in schooling expenditure per se, but by the sorting of teachers and students. We provide extensive evidence of this sorting in Appendix B.3, which points to strong correlations among various school inputs, school value-added and school average test score. Our analysis explains the recurrent findings in the literature on educational finance that "money doesn't matter." Peers and home environments matter.

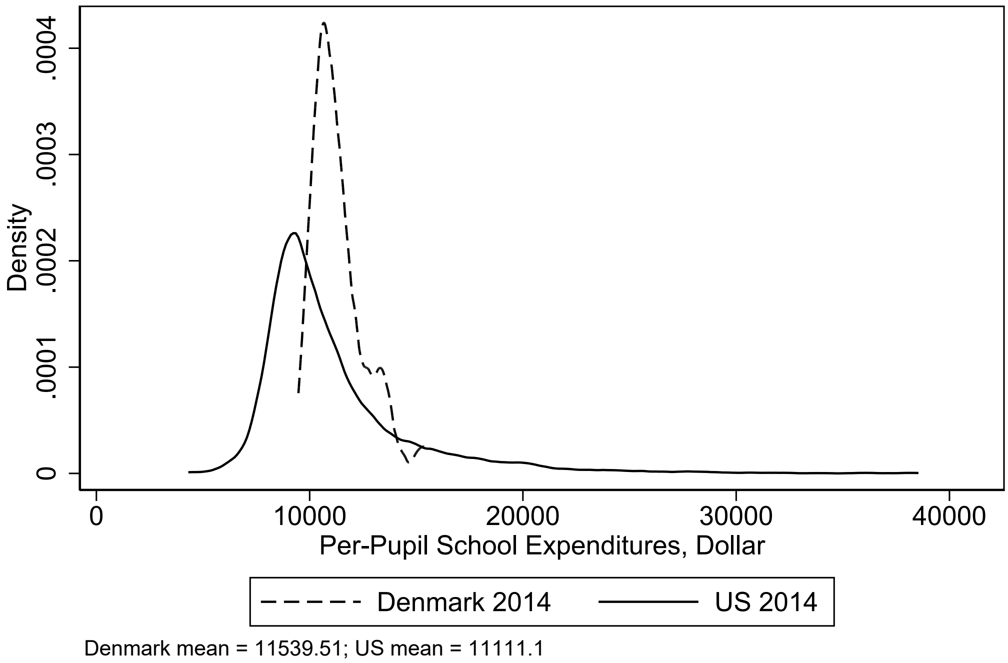
Access to public schools in Denmark is residence-based. Each housing unit is part of a school catchment area assigned to a single school. Parents can defy school catchment area rules in certain cases, although the possibility of doing so is contingent on available capacity in alternative schools. We test the sensitivity of our estimates to non-compliance with initial assignments and find that they are robust.

Figure 1 of Appendix A.1 shows the variation in our measure of school quality (average test scores), in our various specifications reported in Table 1. Despite equal per pupil school expenditures and teacher salaries, there is a great deal of variation in performance of peers across schools, which is due to the spatial sorting of families (and teachers) along the residence-based assignment of students to public schools.

3 Methodology

This section presents a regression framework to recover estimates of the WTP for school quality (measured by test scores), in the presence of household sorting. We use hedonic models to analyze housing prices. An equilibrium is obtained when supply equals demand at each traded quality. The hedonic price function $P(\boldsymbol{z})$ is defined for $\boldsymbol{z} = (z_1, z_2, \ldots, z_n)$, vector of attributes of housing. In our context, $\boldsymbol{z}$ includes neighborhood public services such as local school quality. The gradient of the hedonic price function with respect to school quality is the equilibrium differential that allocates individuals across locations. Locations with lower-quality amenities such as low school and peer quality are predicted to have (*ceteris paribus*) lower housing prices. In this framework, at each point on a hedonic price function, the marginal prices of housing

Figure 1: Comparing Per-Pupil School Expenditure across Municipalities in Denmark and the US (2014 US Dollar)



Notes: This figure shows the average per-pupil school expenditures in public schools in 2014 for the US and Denmark.

characteristics are individual consumer's marginal willingness to pay for that bundle of characteristics *for those at the point of evaluation*. A long line of research using hedonic demand models builds on Tinbergen (1956) and Rosen (1974) and includes Epple (1987), Ekeland, Heckman, and Nesheim (2004), Bajari and Benkard (2005), and Heckman, Matzkin, and Nesheim (2010). See Sieg (2020) for a recent definitive survey.

3.1 Hedonics

Our main estimating equation relates house prices to a vector of housing and neighborhood characteristics, including school quality.[6] We add a set of cluster fixed effects to control for unobserved neighborhood heterogeneity and estimate the following he-

[6]Figure 2 of Appendix B.1 presents the relationship between property values at the school level and school quality.

donic price regression assumed to be linear in its arguments:[7]

$$\ln(p_{imkt}) = \alpha + \beta S_{mkt} + \boldsymbol{\gamma_1'} \boldsymbol{H}_{imkt} + \boldsymbol{\gamma_2'} \boldsymbol{X}_{imkt} + \rho_{kt} + \varepsilon_{imkt}, \tag{1}$$

where $\ln(p_{imkt})$ denotes log property values of individual i who attends school m in cluster k in cohort t. S_{mkt} denotes our measure of school quality for school m in cluster k. Housing and neighborhood characteristics are denoted by $\boldsymbol{H}_{imkt}$ and $\boldsymbol{X}_{imkt}$,[8] as well as neighborhood-by-cohort fixed effects, ρ_{kt}. Finally, ε_{imkt} represents unobserved neighborhood and housing attributes assumed to be iid for a given t and uncorrelated with the regressors. We henceforth use a compact notation and define $\boldsymbol{\mathcal{Z}} = [S, \boldsymbol{H}, \boldsymbol{X}, \rho]$, so $\ln(p_{imkt}) = \boldsymbol{\omega' \mathcal{Z}} + \varepsilon$.

3.2 Proximity Theorem

One method for recovering the WTP for school quality relies on the proximity theorems of Fisher (1966). Given the granularity and richness of our data, they provide a useful framework for estimating Equation (1).

Theorem 1 (Proximity Theorem, Strong and Weak)**.** *Let $\boldsymbol{\omega}^0 = (\boldsymbol{\alpha}^0, \boldsymbol{\beta}^0, \boldsymbol{\gamma}_1^0, \boldsymbol{\gamma}_2^0)$ be the true parameters of model (1). Assume the model is full rank. Define $\hat{\boldsymbol{\omega}}$ as the OLS estimator. The strong proximity theorem asserts that $\operatorname{plim} \hat{\boldsymbol{\omega}} \to \boldsymbol{\omega}^0$ as $\frac{\operatorname{var}(\varepsilon)}{\operatorname{var}(\boldsymbol{\omega' \mathcal{Z}})} \to 0$. A weak form asserts that $\operatorname{plim} \hat{\boldsymbol{\omega}}' \to \boldsymbol{\omega}^0$ as $\frac{\operatorname{cov}(\boldsymbol{\mathcal{Z}}, \varepsilon)}{\operatorname{var}(\boldsymbol{\omega' \mathcal{Z}})} \to 0$.*

The least squares estimator of ω^0 is consistent if (1) the variance of the disturbance is small relative to the observables or (2) if the probability limit of the correlation between the disturbances and regressors is small. Our cluster fixed effect strategy controls for neighborhood sorting at a very local level, so application of this method is plausible in our data. Our approach for identifying $\boldsymbol{\omega}^0$ is valid in large samples if the variance of the

[7] We also run a local linear regression of this specification in Appendix F. We show that the log-linear specification used in the main text accurately represents the price function.

[8] Housing characteristics include the type of building, the number of floors, the number of units per building, the number of bedrooms, toilets, and bathrooms, the size of the living area, and the age of the property. Neighborhood characteristics include household gross income and education, as well as fraction married, intact family, crime, and foreigners.

residual disturbance term in the hedonic equation is relatively small or its correlation with regressors is weak.[9]

To gain intuition, consider a simple least squares estimator of bivariate regression $Y = \tau Q + U$, $E(U) = 0$, $\mathrm{var}(U) > 0$ with finite variances. Under independent sampling, the probability limit of the least squares estimator $\hat{\tau}$ for τ converges to

$$\mathrm{plim}\hat{\tau} = \tau + \frac{\mathrm{cov}(Q, U)}{\sigma_Q^2}.$$

σ_Q^2 denotes the variance of Q. Q may be correlated with U. If $\frac{\mathrm{cov}(Q,U)}{\sigma_Q^2}$ is small, the result follows. Alternatively, if the variance of U is "small" relative to that of Q, $\mathrm{plim}\hat{\tau} \to \tau$.

A test for the validity of the proximity theorem is that as the geographic unit studied becomes smaller, the R-squared of the hedonic regression should increase. We conduct this test, and confirm the hypothesis. Another test applies in the spirit of Altonji et al. (2005) to our hedonic framework.[10] Our estimates are robust to the presence of selection on unobservables within reasonable ranges of assumptions about the importance of unobservables.

The framework presented here allows us to recover preference estimates for measured school quality. The key assumptions justifying our estimate of the impacts of school quality are (1) that the variance of the housing characteristics is relatively "small" within clusters within our common school boundaries (the strong form of Theorem 1) and (2) that our measures of neighborhood composition, education, and income included in the regression "adequately" control for the sorting across boundaries (required by the weak form of Theorem 1).

3.3 Sorting

Sorting is the essential feature of hedonic models. Recovering the mean preferences of heterogeneous agents is a challenge. For instance, if individuals who highly value school quality live in areas with better schools, the marginal WTP likely reflect the pref-

[9]Estimation based on fixed effects implicitly invokes the proximity theorem in that it assumes all essential heterogeneity within the unit represented by the fixed effect is negligibly small.

[10]We conduct their test in Section 6.4.8.

erences of this group. With heterogeneous tastes, the marginal WTP does not align with the average WTP over all groups. Section 7 provides a test for whether our estimates are biased due to household selection on preferences into neighborhoods. We control for selection into schools and neighborhoods using a mixed continuous-discrete model of sorting and housing prices.

4 Data

We use administrative data from Statistics Denmark for the whole population. We focus on five cohorts of ninth graders, who attended ninth grade between 2002 and 2006 and whose biological parents are homeowners. In what follows, we describe in more detail the key variables used in our analysis.

Our analyses of the WTP uses two measures of property prices, based on governmental valuations[11], as well as transaction prices. In both cases, it is defined as the price of the property owned by the biological parents. It is measured at the start of the school year in which the final exam is passed, taken on average at age 16. We drop all outliers of housing values below the first or above the 99th percentile (keeping observations with house prices above $44,000 and below $2.5 million (2010 USD)).[12]

In our sample, the average time spent in a house is 11 years. About 40% of our sample never moves after the child is born. About 30% move only once and end up living on average 8 years in the house.[13] Thus, most parents with children spend their school-age exposure (10 years) living in the same house.[14] We do not have the full history of schools attended by children. We use data on ninth graders. The data for lower grades is only available for a few years. Based on this limited data, we estimate mobility to be around 5%–10% a year between grades 2 and 9.

[11]Government valuation is computed based on sales of other housing units in the relevant market and adjusted for specific characteristics of the property (such as its square footage).

[12]An exchange rate of 6.7 DKK per US dollar is used to obtain the dollar values.

[13]See Appendix C.

[14]See appendix C for the distribution of the number of years spent in the home conditional on the number of times moved for this sample.

School Quality Measures Different types of measures of school quality have been used in the literature, including output-based, input-based, and value-added measures. Value-added measures require tracking of students' performance over time. Brasington (1999), Downes and Zabel (2002), and Brasington and Haurin (2006) find little evidence that such measures are capitalized into house prices. Input-based measures, such as per-pupil spending also have weak effects on housing prices (Hanushek, 1986, 1997). This has led to the use of output-based measures, which are our main measures of school quality. In particular, test scores (broken down by subject) at the school level are available to all in Denmark and advertised on home buying websites.[15] We average student grades on exams taken in their last year of compulsory education. These are national exams on a wide range of subjects, most taken at age 16.

Appendix B.3 discusses a number of measures that capture peer effects, including average school student characteristics, such as parental income or education. We also create school aggregates of teacher quality, based on their college performance, tenure at the school, age graduation from college and an index of quality[16]. Finally, we construct a measure of school value-added. We show the strong correlation between all of these measures and our main measure of school quality, namely average test scores. This should not come as a surprise, given the strong household sorting we uncover in this paper. In light of this, we do not attempt to separately estimate the effects of these variables on house prices. We use our measure of average test scores to quantify school quality considered as a bundle of attributes in the remainder of this paper. Importantly, we are still able to abstract from the role of school expenditure, which is a key contribution of our work.

Defining Neighborhoods Throughout the paper, we use various definitions of neighborhoods. Table 2 provides brief description of these neighborhoods as well as the

[15]See for instance www.dingeo.dk.

[16]This index is based on Gensowski et al. (2021). Using administrative records, all employees in teaching positions in schools between 2009 and 2016 are matched to their (a) academic records from high school (grades in Danish and Mathematics exams) and university as well as (b) employment records to identify unemployment spells. Children's GPA are then regressed on these teacher's characteristics. A national rank of school quality is then generated using linear regression.

numbers each type of sample.

Table 2: Alternative Neighborhood Definitions

Neighborhood Definition	#	Description
Region	5	Below federal level. Supersedes municipalities.
Municipality	270	Each municipality lies within a specific region.
School Catchment Area	1475	Each school catchment area contains a single school.
Parish	1561	A neighborhood formed around a specific church.
Cluster	2215	See below for details.
Small Cluster	8008	See below for details.

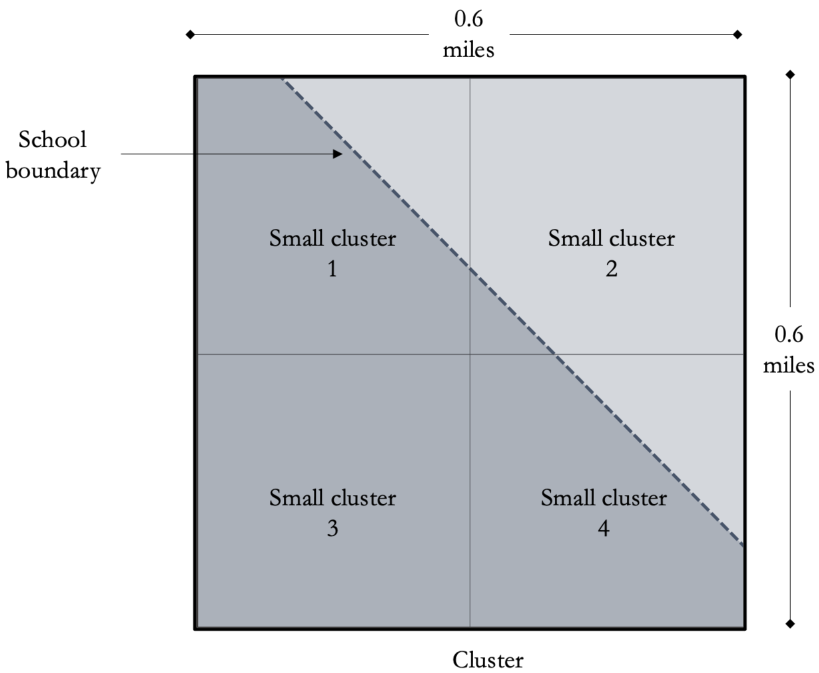
Notes: Number and definition of different neighborhood concepts in Denmark.

Figure 2 provides a visual depiction of the neighborhood partitions we use to recover estimates of the WTP for measured school quality. Our main specification uses variation in housing prices and school quality within clusters.[17] Variation in school quality arises from boundaries of school catchment areas within different clusters. Figure 2 depicts, schematically, a cluster which contains four small clusters. The two shades of blue denote two different school catchment areas which are bordered by the dashed line. The median cluster spans an area of 0.34 square miles and comprises of 985 households, while the median small cluster spans 0.08 square miles and comprises of 245 households in 2004.[18]

[17]In the remainder of this paper, we sometimes refer to these clusters as "neighborhoods".

[18]Further summary statistics and details on the construction of these clusters and expansion to different years are discussed in Appendix A.3.

Figure 2: School Catchment Areas and Clusters



Notes: This figure depicts one cluster, with boundaries of the four small clusters represented with solid lines. The dashed line represents the boundary of two school catchment areas, which are illustrated in two different shades of blue. The variation in school quality we utilize, arises from variation in school catchment area boundaries crossing within clusters.

In constructing clusters, we build on the research of Damm and Schultz-Nielsen (2008), from 1985 to 2004, which is based on the following criteria: (1) clusters correspond to geographical areas within which an individual has social contact[19]; and (2) they remain the same over time.[20] Damm and Schultz-Nielsen (2008) construct clusters on the basis of 431,233 hectare cells (100m x 100m) which exhaust Denmark's surface area. They aggregate these cells to meet confidentiality requirements in terms of the number of households per cluster.[21] Clustering is defined based on housing type and ownership information.[22]

[19]In practice, this implies that two neighbors separated by physical barriers such as water, large roads or forests, would not be included in the same cluster.

[20]These clusters define geographic areas which do not vary over time. Their composition varies as individuals move in and out of the cluster.

[21]Cluster sizes need to have at least 150 households for analyses of residential segregation and a minimum of 600 households for descriptive purposes, as required by Statistics Denmark.

[22]Housing type in the register data is divided into four categories: farmhouse or detached house; townhouse or small block of flats; large block of flats; second home or other house. Ownership information is also broken down into four categories, namely private ownership, privately owned rental, publicly owned rental and private cooperative housing. In the calculation of which hectare cell is most

Moreover, visible features and geographic barriers such as lakes, forests or major roads were used in defining the different boundaries between clusters (which is not always possible in less dense areas). This ensures that within cluster differences in house prices are not driven by these barriers.

Control variables To complement our data on school quality and property values, we use Denmark's rich administrative data to capture a wide range of characteristics at a small neighborhood level.[23] Given household propensities to sort across neighborhoods, even within the clusters considered, these variables allow us to reduce any potential bias arising from sorting. More specifically, we use variables pertaining to the household, including income,[24] education level,[25] crime[26], family structure[27] and ethnicity[28]. We aggregate these measures both at the small cluster level and at the small-cluster-by-school-district level, for our analyses in Section 6.4.1.[29] Moreover, we include a host of housing characteristics.[30]

5 Neighborhood Composition

5.1 Neighborhood Homogeneity

Before reporting our estimates, we discuss in detail how controlling for cluster fixed effects deals with housing and neighborhood heterogeneity. We show that in terms of housing attributes, both sides of the school boundaries within clusters are very similar.

similar, the latter is given a weight of 70%, while the former 30% in forming homogeneous clusters.

[23]We provide summary statistics in Appendix A.4.

[24]We use gross household income excluding transfers.

[25]We use years of completed education. When computing small neighborhood education level, we first compute the maximum number of years of education at the household level. We then aggregate at the small cluster level.

[26]We use an indicator for whether an individual as committed a crime or not in a given year. We exclude traffic related crimes.

[27]We include a measure of marital status and intact family structure. For the latter, a family structure is considered intact if during the first 18 years of a child being born, both parents are present.

[28]We distinguish between foreigners and non-western foreigners. The former denotes individuals who have at least one parent not born in Denmark. Non-western foreigners are individuals who have at least one parent from a non-western country.

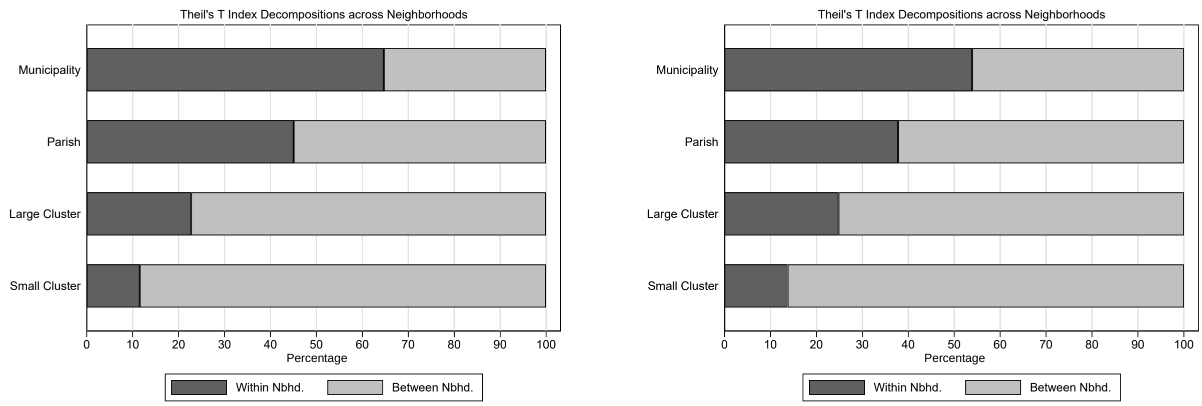
[29]We report the correlation between the different neighborhood attributes in Appendix A.2.

[30]For example, type of building, the number of floors, the number of units per building, the number of bedrooms, toilets and bathrooms, the size of the living area and the age of the property.

To analyze the spatial decomposition of inequality in housing types and characteristics across neighborhoods in Denmark, we use Theil's T Index. We focus on two characteristics of buildings across neighborhoods: the number of apartments in the building, and the number of floors. Figure 3 shows the decomposition across neighborhoods by different units of neighborhood, i.e., municipality, parish, cluster, and small cluster levels. Panel (a) analyzes the number of apartments in each property. At the municipality-level, only about 35% of inequality can be contributed to between-neighborhood component. The share of the between-neighborhood component increases to about 90% when we analyze the inequality in small clusters.[31] Panel (b) considers the number of floors of each property.

Figure 3: Theil's T Decomposition of Housing Characteristics across Neighborhoods

(**a**) Number of Apartments (**b**) Number of Floors



Notes: This figure presents the Theil's T decomposition of building characteristics across different neighborhood units in Denmark. Panel (a) focuses on the number of apartments and Panel (b) shows the statistics for the number of floors. See Appendix E for details.

The results presented in Panels (a) and (b) suggest that the share of within-neighborhood inequality decreases from about 55% to less than 15% when focusing on small neighborhoods rather than the municipalities. These results suggest that the housing types in our narrowly-defined neighborhood units do not vary "much" and the variation in house prices is not driven by differences in the housing structure. We reach a similar conclusion when instead of the Theil's decomposition we use a simple variance decom-

[31] Appendix E discusses how we use Theil's T Index to compute within- and between-neighborhood inequality.

position.[32] Our rich set of housing characteristics in our hedonic regression control for such differences that may affect house prices.[33]

5.2 Neighborhood Sorting

The previous section provides evidence on the relative homogeneity of our clusters with respect to housing characteristics relative to broader neighborhood concepts, such as municipalities. In this section, we explain the variation that still remains. In line with our identifying assumptions, we show that housing characteristics are relatively homogeneous within clusters. This should not come as a surprise, given that the algorithm generating these clusters minimizes the within variance in housing types. Nonetheless, there is strong sorting of individuals based on their characteristics, as well as the characteristics of the neighbors. This is in line with our analysis in Appendix E, which shows that although clusters are relatively homogeneous, there is a still significant variation within clusters. Thus, the remaining heterogeneity may be driven by sorting across school boundaries, which occurs even within clusters. This emphasises the need to control for small neighborhood characteristics in hedonic price regressions.

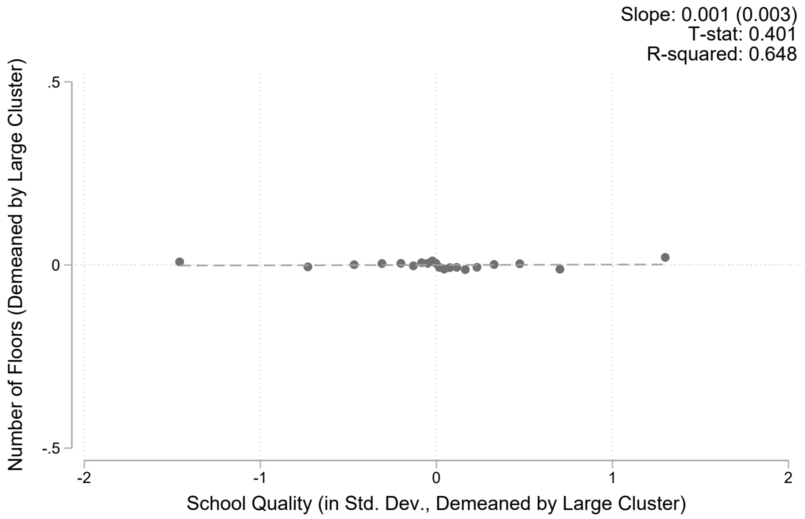
To assess the level of sorting within clusters in Denmark, we plot the relationship between measured school quality and different attributes, both at the individual and household level after controlling for neighborhood-by-cohort fixed effects. This analysis provides a test of our identifying assumption—unobserved neighborhood attributes should not vary within clusters. We first show in Figure 3 that housing prices are positively related to school quality so that the relationship we are investigating is empirically relevant. In Figures 4 and 4, we show that conditional on small neighborhood characteristics, and neighborhood-by-cohort fixed effects, housing characteristics are largely uncorrelated with differences in school quality across schools. This suggests that the neighborhoods we study are relatively homogeneous, at least with regards to the make up of their housing characteristics.

[32]See Figure 20.

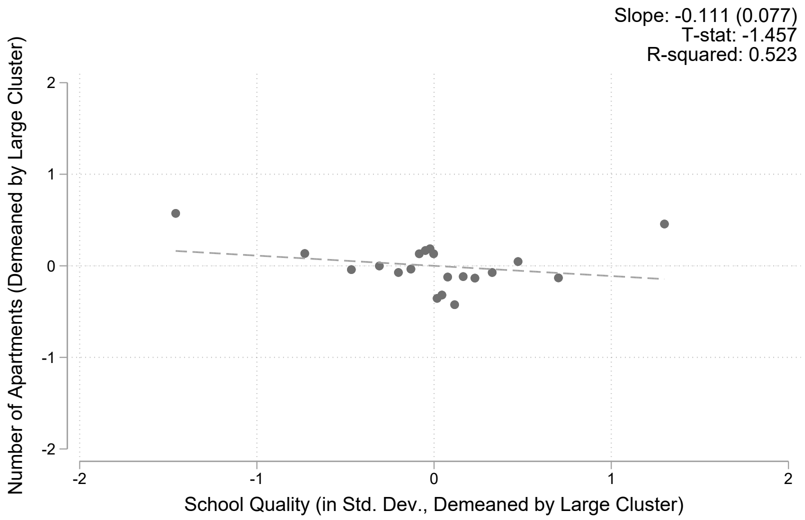
[33]We also analyze the spatial decomposition of income inequality across neighborhoods in Denmark using the Theil's T Index in Appendix E.

Figure 4: Sorting within Clusters (Housing Characteristics)

(**a**) Number of Floors



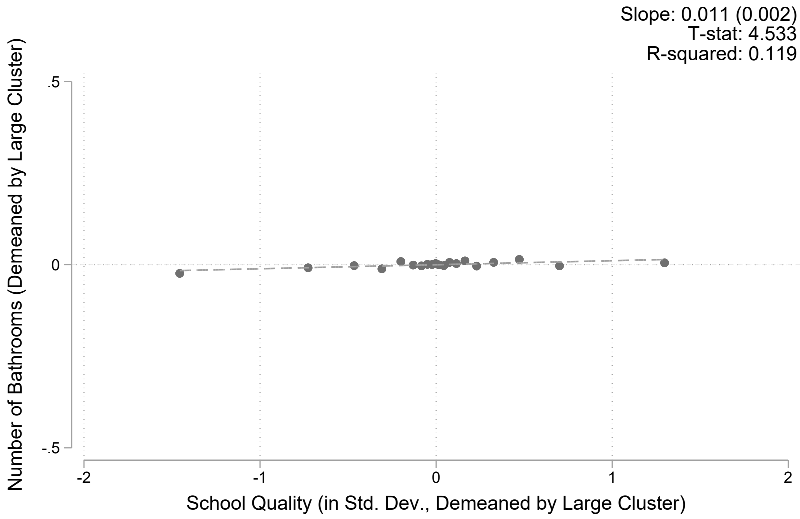
(**b**) Number of Apartments



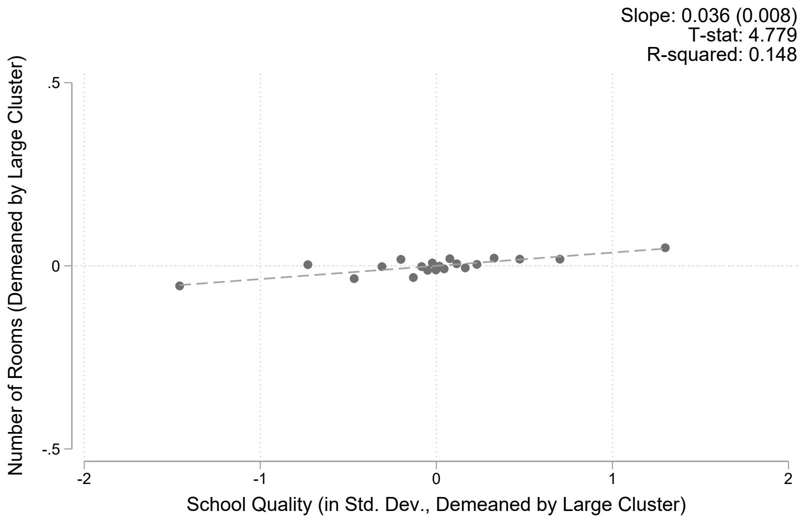
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between demeaned housing characteristics and demeaned school quality within clusters. Each panel is constructed by regressing various housing characteristics on school quality, controlling for neighborhood-by-cohort fixed effects and small neighborhood attributes—average income, years of education, fraction married, non-westerners, foreigners, crime, and non-intact households. Standard errors corrected for clustering at the cluster-cohort level are reported in the top right corner.

Figure 4: Sorting within Clusters (Housing Characteristics), Cont'd

(**c**) Number of Bathrooms



(**d**) Number of Rooms



Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between demeaned housing characteristics and demeaned school quality within clusters. Each panel is constructed by regressing various housing characteristics on school quality, controlling for neighborhood-by-cohort fixed effects and small neighborhood attributes—average income, years of education, fraction married, non-westerners, foreigners, crime, and non-intact households. Standard errors corrected for clustering at the cluster-cohort level are reported in the top right corner.

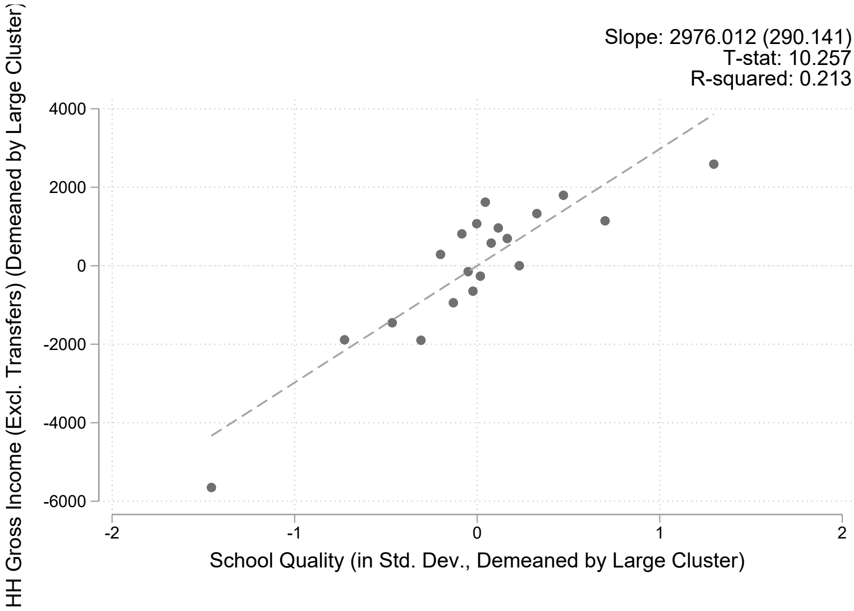
Households sort across neighborhoods in Denmark, based on their preferences for vectors of neighborhood attributes. This is evidenced by the relationship between individual characteristics, as well as small neighborhood characteristics with school quality, within clusters. On average, households living in higher test score school catchment areas (within clusters), have higher gross income, education and more stable family structures, as seen in Figures 5 and 5. Moreover, within clusters, the small neighborhoods associated with a better school catchment area, are on average more educated, have higher income and more stable family structures, while having less criminality and a smaller fraction of western or non-western foreigners.[34] Overall, this evidence showcases the importance of controlling for unobserved neighborhood characteristics through our cluster fixed effects strategy as well as small neighborhood attributes.[35]

[34]See Figures 6 and 7.

[35]Clusters with single schools are dropped from the analysis, since there is no variation in school quality remaining.

Figure 5: Sorting within Clusters (Individual Characteristics)

(**a**) Gross Income excluding Transfers



(**b**) Years of Education

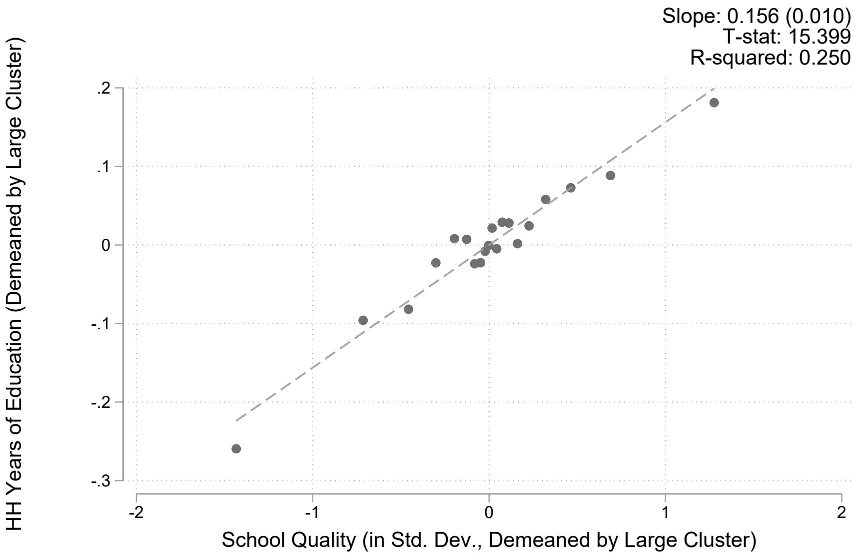
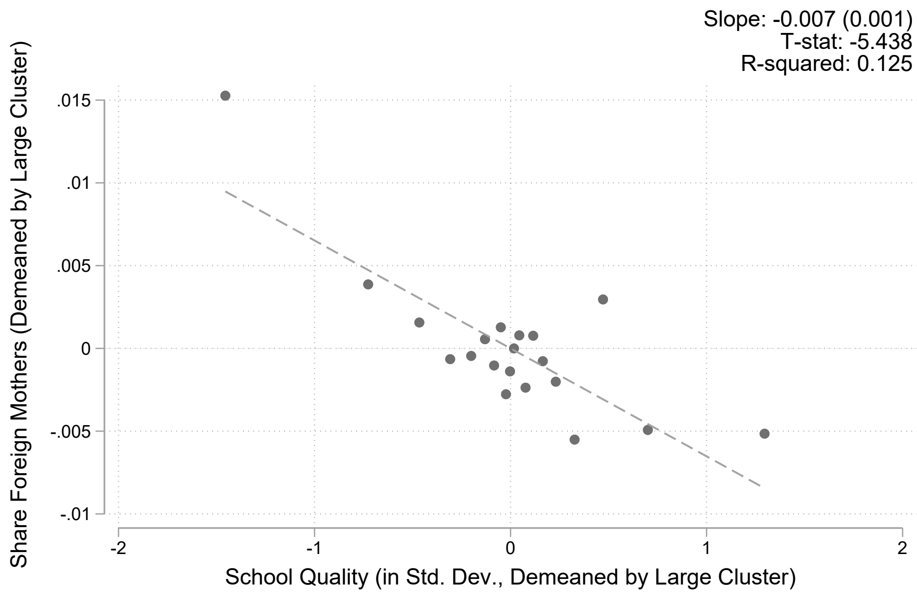


Figure 5: Sorting within Clusters (Individual Characteristics), Cont'd

(c) Foreign Mother



Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between demeaned individual characteristics and demeaned school quality within clusters. Each panel is constructed by regressing various individual characteristics on school quality, controlling for neighborhood-by-cohort fixed effects, small neighborhood as well as housing attributes—the type of building, the number of floors, the number of units per building, the number of bedrooms, toilets and bathrooms, the size of the living area, and the age of the property. Standard errors corrected for clustering at the cluster-cohort level are reported in the top right corner.

5.3 Fixed Effects and Unobserved Preferences for Local Amenities

Section 5.1 gives evidence suggesting that sorting is somewhat stronger in smaller geographic units. Section 5.2 documents that families sort into schools given their local neighborhood units, while their access to other amenities does not vary within the small geographic units by design. Our hedonic approach exploits a fixed effect model to account for unobserved preferences for neighborhood amenities and public goods. In this section, we show that the unexplained variation in house price decreases with the granularity of the geographic units. This gives credibility to our estimation strategy for identifying the WTP parameter, using the Proximity Theorem discussed in Section 3. To do so, we analyze the R-squared of a set of regressions of house prices on school quality, with fixed effects at different neighborhood-by-cohort levels. To define the neighborhood unit, we use five alternatives, namely regions, municipality, parish, cluster, and small cluster (by diminishing order of size).

Table 3: R-SQUARED FOR REGRESSIONS OF LOG HOUSING PRICE ON SCHOOL QUALITY WITH FIXED EFFECTS (FE) AT VARIOUS NEIGHBORHOOD LEVELS

	Region FE	Munic. FE	Parish FE	Cluster FE	Small Cl. FE
	(1)	(2)	(3)	(4)	(5)
Without controls					
Full Sample	.19	.28	.35	.37	.52
Copenhagen Area	.19	.27	.37	.54	.71
With controls					
Full Sample	.45	.48	.53	.54	.64
Copenhagen Area	.48	.51	.55	.65	.76
# FEs (full sample)	25	1,341	7,521	9,982	31,619

Notes: Column (1) presents the R-squared of the regression of house prices on school quality using a region-by-cohort fixed effect model. Column (2) presents the R-squared of the regression of house prices on school quality using a municipality-by-cohort fixed effect model. Column (3) reports the R-squared of the regression of house prices on school quality using a parish-by-cohort fixed effect model. Column (4) shows the R-squared of the regression of house prices on school quality using a cluster-by-cohort fixed effect model. Column (5) presents the R-squared of the regression of house prices on school quality using a small cluster-by-cohort fixed effect model. We present two sets of results – with and without neighborhood and housing controls. For each of these specifications we provide the corresponding number of area-by-cohort fixed effects for the full sample. We also provide a breakdown of the R-squared for the full sample as well as for a subset of our data focusing on the Copenhagen metropolitan area.

Table 3 shows that, consistent with our argument based on the Proximity Theorem, the unexplained variation in house prices decreases when we move towards more narrowly-defined geographic units. For example, the R-squared almost doubles when we shift from a region fixed effects model to a cluster fixed effects model. As Table 3 shows, the R-squared of the regression of house prices on school quality using the micro-level data increases from 0.19 using regions fixed-effects to 0.28 using municipality fixed effects, to 0.35 for parishes, to 0.37 for clusters, and to 0.52 for small cluster fixed-effects.

We further show that our strategy works best in more densely populated areas where the implied sizes of clusters are smaller, sorting is likely to be finer, so adding cluster-level fixed effects more likely controls more for unobserved heterogeneity. Including cluster fixed effects captures 54% of the variation in house prices, which increases to 71% for the small cluster fixed effects specification, more than three times bigger than the variation explained by a broad neighborhood unit (i.e., region) fixed effect. Our approach is more applicable in urban areas, such as the Copenhagen metropolitan area.[36] We show in Section 6.4 that our estimated coefficients are largely the same across geographic areas. In particular, adding covariates to the hedonic regression in the Copenhagen metropolitan area increases the R-squared to 76%.[37]

6 Hedonic Price Regressions

6.1 Cluster Fixed Effects Strategy

Table 4 reports a set of estimates for various econometric specifications. Results from OLS without controls are reported in column 1. A one–standard deviation increase in school test scores is associated with an increase in house prices of 14.7%. Our second OLS specification adds a vector $\boldsymbol{X}$ of small neighborhood characteristics, such as average income and education, as well as housing characteristics $\boldsymbol{H}$. The set of housing characteristics includes the type of building, the number of floors, the number of units per building, the number of bedrooms, toilets and bathrooms, the size of the living area and the age of the property. The coefficient on test scores substantially decreases from 0.14 to 0.02, emphasizing the role of these neighborhoods and housing characteristics on house prices.

We can now turn to our cluster fixed effects strategy, to assess the role of unobservables, in the third and fourth columns of Table 4. Compared to the OLS regression with no covariates, we see that the cluster fixed effects specification significantly reduces the estimated effect of school quality on house prices, demonstrating the importance of controlling for unobserved neighborhood characteristics.

The final column adds both the neighborhood fixed effects, ρ, as well as the small neighborhood and housing characteristics, $\boldsymbol{X}$ and $\boldsymbol{H}$, to recover the marginal WTP

[36] About 32% of the population live in the Copenhagen metropolitan area.

[37] To test whether using government valuations reduces variability in the data, we compare the R-squared of this specification to one using transaction data. Both R-squared are similar.

for school quality. For the average house between 2002 to 2006, our estimate of 2.7% implies that a one–standard deviation increase in average test score increases house prices by about \$6,700,[38] holding housing and neighborhood characteristics constant.[39] In percentage terms, this is a very similar estimate to those found in other countries, such as the US, UK, or France (see Black and Machin, 2011). While the estimates are comparable in magnitude to previous studies in different countries, we interpret ours (and theirs) very differently. Given the equalization of school expenditure in Denmark, households in our sample are paying to attend schools with better peers and teachers, not for school quality measured in the conventional way (e.g. Hanushek, 1997).

[38]This amounts to about \$10,000 at mean house price in 2015, the most recent year of data availability.

[39]We estimate a specification where we add 8th grade average score (for available years – post 2010). The coefficient on 8th grade average score stands at 0.008 and is statistically significant, akin to a precise estimate of 0. In this regression, the coefficient on 9th grade average test score does not vary much compared to one without 8th grade average test score as a regressor (0.026 vs. 0.031 holding the sample identical). This is not a surprise, as 9th grade test scores are much more salient: they determine entrance into upper secondary schools.

Table 4: Regression Results: Comparing OLS and Fixed Effect (FE) Estimates
Dependent variable: Log House Price

	OLS	Controls	Cluster FE	Controls and FE
	(1)	(2)	(3)	(4)
School Quality	0.147***	0.022***	0.040***	0.027***
	(0.005)	(0.003)	(0.003)	(0.002)
Neighborhood characteristics	No	Yes	No	Yes
Housing characteristics	No	Yes	No	Yes
Cluster-Cohort FE	No	No	Yes	Yes
Cohort FE	Yes	Yes	No	No
Observations	126,301	126,291	126,301	126,291
R^2	0.08	0.40	0.37	0.54

Notes: Columns (1) and (2) show an OLS specification as a benchmark, while columns (3) and (4) show two different specifications with cluster-by-cohort as fixed effects. Sample includes all parents in Denmark whose children attend ninth grade between 2002 and 2006 and own a property. Property values are in logs and school quality is standardized such that the coefficients can be interpreted as the WTP, in percentage terms, for a one–standard deviation increase in school quality. Standard errors corrected for clustering at the school-cohort level are reported in parentheses. Neighborhood characteristics include household gross income, and education as well as fraction married, intact family, crime, and foreigners. Housing characteristics include the type of building, the number of floors, the number of units per building, the number of bedrooms, toilets and bathrooms, the size of the living area and the age of the property. Singleton groups (groups where clusters include only one school) were kept, but results are robust to dropping them, as their number is small. In model (4), about half of the explained variation is due to the fixed effects, while the remaining is due to the controls. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The fact that this estimate is substantially lower compared to the estimate obtained from controlling only for neighborhood fixed effects, suggests that households do not just care about their neighborhood at large[40], but much more about local neighborhood attributes and sort on that basis. This finding is consistent with that of Bayer et al. (2007) in the US.

6.2 School Boundary Changes as Exogenous Variation

To confirm the magnitude of our results, we exploit changes in schooling boundaries that occur in Denmark. Our strategy consists in using within old school boundaries-by-small-neighborhood variation in school quality, in the spirit of Billings et al. (2014). The fact that reassigned students live in the same neighborhood reduces potential biases

[40]Recall that the median size of these neighborhoods are around 0.34 square miles.

arising from parents neighborhood selection based on school quality. Still, over time, school boundaries change in ways that parents may not be able to predict. Variation in school quality arises from changes in school boundaries which causes some students within the old school boundary (and within a small cluster) to attend different schools. We fix school boundaries at the earliest time in which we observe them, i.e., in 2006.[41] We then focus on cohorts between 2007 and 2015. Using this estimation strategy, the estimated impact of school quality on house prices is 2.2% (statistically significant, p-value < 0.01)

6.3 Identification Issues

Two potential problems may undermine the identification of school quality and neighborhood capitalization into house prices. First, in the presence of neighborhood sorting, attributes on either side of the school catchment boundary would be strongly correlated, as described in Appendix B.3. This is the case, even within clusters, as we in detail in Section 5.2. This sorting may thus cause the regressors to be collinear, compromising the identification of separate effects of school quality and neighborhood quality. Second, neighborhood controls in the previous regressions could be endogeneous, as we may not be able to capture all attributes that drive the sorting process, yet would impact house prices.

To tackle these issues, let $Q \in \{0, 1\}$ be a variable which is equal to 1 if a household sorts on the high quality side of the school catchment area or 0, if the household sorts on the low quality side, within a cluster.[42] We estimate the following specification:

$$\ln(p_{imkt}) = \alpha + \beta Q_{mkt} + \boldsymbol{\gamma}'\boldsymbol{H}_{imkt} + \kappa_{kt} + \varepsilon_{imkt}, \tag{2}$$

where κ_{kt} denotes a small cluster fixed effect. $\boldsymbol{H}$ denotes housing characteristics.

β can then be interpreted as the payment made by household for living on the high

[41] We note that the sample we use here deviates from the sample used for the main estimating equation, given data availability. We describe how the sample is constructed beyond 2006 and up to 2015 in Appendix A.3.

[42] In this analysis, we keep only clusters that contain two school catchment areas.

quality side of the cluster, which is the payment for neighborhood and school quality. In this case, our estimate stands at 2.8%.[43] This is an upper bound to the sum of the WTP for school and neighborhood quality.[44]

6.4 Extensions and Sensitivity Analyses

This section conducts a sensitivity analysis to show that our main estimates remain robust.

6.4.1 School Catchment Area Boundaries and Immediate Neighbors

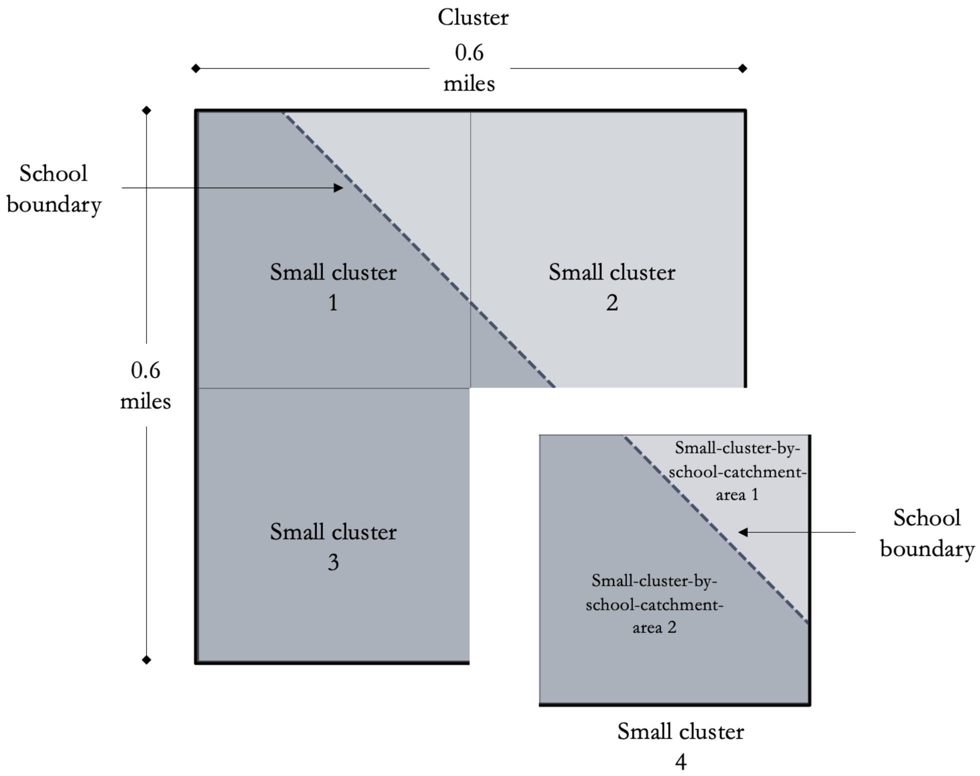
The first set of sensitivity analyses we present addresses the potential concern that school boundaries are not necessarily adjacent within our clusters, given the small geographical area they span. Data on the assigned school catchment area available from 2006 to 2015 allows us to verify that 80% of clusters in that period are composed of at least two distinct school catchment areas. Column (1) of Table 5 reports estimates based on this sample using the same specification as in (1).

About 40% of small clusters have at least one set of adjacent schools. Using these small clusters, we can address the concern that our estimates are potentially biased due to individuals sorting based on characteristics that are even more local than our previously included small neighborhood (median area of 0.08 square miles) covariates. To do so, we replace cluster fixed effects with small cluster fixed effects in Equation (1). Moreover, we replace the small cluster-level characteristics, with attributes computed at the small-cluster-by-school-catchment-area level. Figure 6 visually depicts this strategy. Estimate of the WTP for school quality for such specification is reported in column (2) of Table 5. These include a set of controls for housing attributes, as in our main specification.

[43] We test the null of equality of coefficient between this specification and the main specification and cannot reject the null ($p > 0.9$).

[44] We note that on average, a change from a low to high quality school catchment, within cluster, induces a .8 standard deviation increase in school quality.

Figure 6: School Catchment Areas and Small Clusters



Notes: This figure depicts one cluster, with boundaries of the four small clusters represented with solid lines. The dashed line represents the boundary of two school catchment areas, which are illustrated in two different shades of blue. In this robustness check, we utilize variation in school quality within small clusters and add small-cluster-by-school-catchment-area level characteristics, as depicted in the bottom right corner of the figure.

These two latter specifications are closely related to the idea of Boundary Discontinuity Design (BDD) of Black (1999), since we use only variation in very close proximity to school boundaries. In fact, for the latter specification, which uses small cluster fixed effects, we use variation that is particularly close to the boundary—retaining variation in school quality and house prices that are no further apart than within a 0.08 square miles cluster. In particular, this ensures that houses are not only close to the boundary, but also that they are in close proximity with each other. This is an important benefit of our approach.

Table 5 reports our estimates of these two specifications. We find estimates of 3.2% and 2.8%, respectively, in line with our main specification.

6.4.2 WTP over Time

An important benefit from our strategy is that it does not rely on changes over time in school quality, an issue raised by Kuminoff and Pope (2014). They show that studies that use this strategy need to assume (without providing evidence) that the hedonic price function is constant over periods of years (sometimes decades). Our strategy does not require this assumption. In Appendix D.2, we present results showcasing the temporal variation in the WTP for school quality. We fail to reject the null hypothesis that the WTP over the years we analyze are not statistically different from each other in levels or logs.[45]

6.4.3 Defiers

We address concerns regarding the presence of school catchment area defiers. Defiers are households that live in a specific school catchment area, but send their children to a school in a different school catchment area. Given our data on school catchment between 2006 and 2015, we are able to get a better grasp on the importance of defiers in Denmark, as well as its potential impact on our estimate.

We analyze defiers in two distinct ways.[46] First, we analyze a sample which drops all individuals who do not attend the most frequently attended school in a given large-cluster-by-school-catchment-area (reported in column (3) of Table 5) or in a given small-cluster-by-school-catchment-area (reported in column (4) of Table 5).[47] Second, we drop all cluster-by-school-catchment-areas that have *any* defiers. This leads us to drop about 50% of the sample when using clusters with any defiers, while dropping 25% of the sample when dropping small clusters with any defiers. Results are reported in columns (5) and (6). In all cases, we see that our estimate is robust to these sensitivity checks.

[45] The test of equality of coefficients in levels is conducted after dropping 2007, which is a year where house prices surged in Denmark.

[46] Our data allow us to capture schools attended by students. However, we cannot tell whether this school is the one assigned. This arises because we do not have a mapping between school catchment areas and schools. We therefore devise methods based on most attended schools in narrowly defined geographical areas, as described in the main text.

[47] These specifications drop approximately 15% of individuals.

Table 5: Robustness Checks: School Catchment Areas, Small Cluster Fixed Effects and Treating Defiers

	(1)	(2)	(3)	(4)	(5)	(6)
School Quality	.032***	.028***	.032***	.036***	.034***	.035***
	(0.002)	(0.002)	(0.004)	(0.008)	(0.002)	(0.007)
R^2	.55	.65	.64	.67	.56	.58
Observations	203,769	252,849	84,625	46,329	171,109	49,956

Notes: Table shows estimates from various robustness checks. The sample includes parents in Denmark whose children attend ninth grade in public schools between 2006 and 2015 and own a property. Column (1) shows results from our main specification, using only clusters where school boundaries are crossing. Column (2) presents results of a specification using small cluster fixed effects. Controls include small-cluster-by-school-catchment-area attributes measuring average household gross income, and education as well as fraction married, intact family, crime and foreigners. Housing characteristics include the type of building, the number of floors, the number of units per building, the number of bedrooms, toilets and bathrooms, the size of the living area and the age of the property. Columns (3)–(6) shows our estimates from conducting a subsample analysis aimed at removing defiers, as explained in the text. Property values are logged and school quality is standardized such that the coefficients can be interpreted as the WTP, in percentage terms, for a one–standard deviation increase in school quality. Neighborhood and housing characteristics are as above. Cluster-by-cohort fixed effects are included. Standard errors corrected for clustering at the school-cohort level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.4.4 Transaction Data

Thus far we have used governmental valuations of housing prices. We examine whether using house prices directly from sales data impacts our estimates. We show that they are robust to this different measure of our dependent variable (column (1) of Table 6). We note that since only a fraction of houses are sold on the market every year, the number of observations is smaller for this analysis.

6.4.5 Lags of Quality

Third, we look at the impact of using past values of our school quality measures. We show in column (2) of Table 6 that our main results are robust to using lags of school quality.[48]

[48] Gibbons and Machin (2003) outline the potential endogeneity of school quality when measured by indicators of student performance. A potential test to this is to use lags of school quality, although we note that under serial correlation of unobservables this would be a weak test.

Table 6: Robustness Checks: Sales Data, School Quality Lags, and Distinct Housing Markets

	(1) Sales	(2) Lags	(3) Copenhagen Area	(4) Urban	(5) Rural
School Quality	.034***	.028***	.025***	.028***	.033***
	(0.008)	(0.003)	(0.004)	(0.002)	(0.008)
R^2	.65	.55	.65	.59	.51
Observations	18,027	77,245	14,690	106,410	19,881

Notes: This table shows estimates from various robustness checks. The sample includes parents in Denmark whose children attend ninth grade in public schools between 2002 and 2006 and own a property. Column (1) shows our estimate from using data on property transactions. Column (2) shows results from replacing our variable for school quality by its second lag (using average test score as measure of school quality). Columns (3), (4) and (5) look at housing markets, respectively focusing on the Copenhagen Metropolitan Area, urban and rural areas. Property values are logged and school quality is standardized such that the coefficients can be interpreted as the WTP, in percentage terms, for a one–standard deviation increase in school quality. Neighborhood and housing characteristics are as above. Cluster-by-cohort fixed effects are included. Standard errors corrected for clustering at the school-cohort level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.4.6 Copenhagen Metropolitan Area

Finally, we look at the sensitivity of our estimates to the choice of different geographic areas. Column (3) of Table 6 shows estimates for the Copenhagen Metropolitan Area. The estimated coefficient is 2.5%, while the R-squared increases to .65. Our fixed effects strategy works better in more urban and denser areas, as we are able to better characterize heterogeneity.

6.4.7 Urban and Rural Areas

Turning to columns (4) and (5), we find that our estimates are very robust to focusing only on urban or rural areas.[49] Interestingly, a specification as in column (3) but without cluster fixed effects produces an estimate of the WTP for school quality of 5.1%, whereas in columns (4) and (5), the OLS estimate is lower compared to a fixed effects model (1). This provides evidence of the differential nature of unobserved attributes and their effect on prices and school quality, across places, in Denmark.

[49] The definition of the United Nations is here used, where urban (as opposed to rural) denotes a built-up area with at least 200 inhabitants, where the distance between the buildings is not more than 200 metres, unless interrupted by public facilities, such as parks.

6.4.8 Selection on Unobservables

We conclude this section on robustness by applying a recently proposed method by Diegert et al. (2022) to bound our estimates in the presence of selection on unobservables. This method generalizes the adaptation of the Altonji et al. (2005) method by Oster (2019), since it allows for endogenous omitted varaibles. We provide a brief overview of this approach in Appendix G. We implement the methodologies of Diegert et al. (2022) on the model presented in 6.4.1, where our estimate of the effect of school quality on house prices is least likely to be confounded by unobservables, since we include fixed effects at the most granular level possible (small cluster level fixed effects). The method is based on the assumption that the variable of interest (school test scores) is less strongly correlated with omitted variables than with observed variables. It applies the standard omitted variable bias formula to determine the strength of the correlation between the unobservables and the variables of interest that is required to make a population OLS estimated of the parameter of interest (the impact of school quality on house value) zero.

Our estimates are robust in the sense that the strength of the correlation between the variables of interest and unobservables has to be greater than 61% of that of the correlation with observables. Given the wealth of our data and the high values of R^2 for the fitted values, this magnitude seems implausibly high.[50]

7 Controlling for Selection Both into Neighborhoods and Schools

This section applies a methodology that tackles the issue of selection into both neighborhoods and schools, jointly, which requires dealing with the polychotomous nature of the choice. We estimate a selection model where individual i makes a choice, k, among K different alternatives, i.e., clusters. Assume i chooses k, and we observe in-

[50]The Diegert et al. (2022) breakdown point cannot be larger than 100%. See Appendix G for more details. We derive another breakdown point using the framework of Oster (2019) and reach the same conclusion. See Appendix G.

dividual i's property value only for cluster k.[51]

The hedonic price regression for individual i in school m, is[52]

$$\ln(p_{ik}) = \alpha_k + \beta_k S_m + \boldsymbol{\delta_k'} \boldsymbol{X_i} + u_{ik}$$

where p_{ik} is house prices in chosen cluster k, α_k is a cluster level specific constant, S_m measures school quality, $\boldsymbol{X_i}$ is a vector of housing characteristics, and u_{ik} is an error term.[53] Individual utilities, V_{ik}, are specified as follows:

$$V_{ik} = \boldsymbol{\gamma_k'} \boldsymbol{Z_i} + \eta_{ik}, \qquad k = 1, \ldots, K \tag{3}$$

where k is a categorical variable that describes the choice of an economic agent among K cluster alternatives based on utilities V_{ik}. Finally, η_{ik} is an error term.

The vector $\boldsymbol{Z_i}$ includes neighborhood characteristics, including school quality, average income, years of education, fraction married, non-westerners, foreigners, crime, and non-intact households. We assume that the model is non-parametrically identified from exclusion of some of the variables in $\boldsymbol{Z_i}$ from the variables in $\boldsymbol{X_i}$; we let $\boldsymbol{Z_i}$ include a dummy capturing whether each child lives in the same alternative (cluster) as their grandparents. The exclusion restriction for the identification purpose is that an individual's house price does not depend on whether their parents live in the same cluster. This specification allows individuals to have preferences for living close to their parents as well as the cluster characteristics, but restricts mean house price to be a function only of cluster characteristics in which the house is located.[54]

Without loss of generality, the outcome variable $\ln(p_{ik})$ is observed if and only if cluster k is chosen, which happens when $V_{ik} > \max_{l \neq k}\{V_{il}\}$.

Now, define:

[51] Domencich and McFadden (1975).

[52] To simplify notation we abstract from cohort subscripts, t.

[53] In this specification of the model, we abstract from other neighborhood attributes (such as average neighborhood income), which may themselves be endogeneous and would require further exclusion restrictions to be identified. These attributes of the neighborhood are included in the selection Equation (3).

[54] We also consider an alternative exclusion restriction, where we fix the location of the grandparents at the time the child is born. We find very similar estimates.

$$\varepsilon_{ik} = \max_{k \neq l}\{V_{il} - V_{ik}\} = \max_{k \neq 1}\{\boldsymbol{\gamma_l'Z_i} + \eta_{il} - \boldsymbol{\gamma_k'Z_i} - \eta_{ik}\} \tag{4}$$

which is equivalent to $\varepsilon_{ik} < 0$.

Assuming that the η_{ik}'s are independent and identically Gumbel distributed, we obtain the multinomial logit model of McFadden (1974):

$$P_k \equiv P(\varepsilon_k < 0 \mid \boldsymbol{Z}) = \frac{\exp(\boldsymbol{\gamma_k'Z_i})}{\sum_l \exp(\boldsymbol{\gamma_l'Z_i})}$$

where P_k the probability that neighborhood k is preferred.

Based on this expression, consistent maximum likelihood estimates of the γ_l's are easily obtained. The problem is to estimate the parameter vector β_k while taking into account that the disturbance term u_{ik} may not be independent of all η_{il}'s. This introduces some correlation between the explanatory variables and the disturbance term in the hedonic price regression. Because of this, least squares estimates of β_k, our parameter of interest, would not be consistent.

Define $\boldsymbol{\Gamma}$ as follows:

$$\boldsymbol{\Gamma} = \{\boldsymbol{\gamma_1'Z_i}, \boldsymbol{\gamma_2'Z_i}, \ldots, \boldsymbol{\gamma_K'Z_i}\}$$

Generalizing the model from Heckman (1979), bias correction can be based on the conditional mean of u_k :

$$\mathbb{E}\left(u_k \mid \varepsilon_k < 0, \boldsymbol{\Gamma}\right) = \iint_{-\infty}^{0} \frac{u_k f\left(u_k, \varepsilon_k \mid \boldsymbol{\Gamma}\right)}{P\left(\varepsilon_k < 0 \mid \boldsymbol{\Gamma}\right)} d\varepsilon_k du_k = \lambda(\boldsymbol{\Gamma})$$

where $f\left(u_k, \varepsilon_k \mid \Gamma\right)$ is the conditional joint density of u_k and ε_k.

Given that the relation between the K components of Γ and the K corresponding probabilities is invertible, there is a unique function μ that can be substituted for μ such that:

$$\mathbb{E}\left(u_k \mid \varepsilon_k < 0, \boldsymbol{\Gamma}\right) = \mu\left(P_1, \ldots, P_K\right)$$

Therefore, consistent estimation of β_k can be based on one of two regressions:

$$\ln(p_{ik}) = \alpha_k + \beta_k S_m + \boldsymbol{X_i'\delta_k} + \mu\left(P_1, \ldots, P_K\right) + w_{ik} \tag{5a}$$

$$= \alpha_k + \beta_k S_m + \boldsymbol{X_i'\delta_k} + \lambda(\boldsymbol{\Gamma}) + w_{ik} \tag{5b}$$

where w_{ik} is a residual that is mean-independent of the regressors.

Semi-parametric estimation of this model confronts the curse of dimensionality. Whenever the number of alternatives is large it implies the estimation of a large number of parameters, rapidly making it intractable for practical implementation.[55] Thus, restrictions over $\mu(P_1, \ldots, P_K)$, or equivalently $\lambda(\boldsymbol{\Gamma})$, are required. Different papers in the literature (Dahl, 2002; Dubin and McFadden, 1984; Lee, 1983) impose different assumptions for the bias correction. In this paper, we follow Dahl (2002), and one based on index sufficiency as in Equation (5b).

7.1 Results

In this section, we present estimates of the effect of school quality on house prices, controlling for the selection of households to cells in various ways.

Below we implement several methodologies, based on Equation (6):

$$\ln(p_{ik}) = \alpha_k + \beta_k S_m + \boldsymbol{X_i'\delta_k} + \mu(\Lambda) + w_{ik} \tag{6}$$

where as above p_{ik} and S_m respectively denote house prices and school quality, measured by average test scores.

We estimate three models:

1. A cluster-by-cluster OLS specification of log house prices on school quality (average test score) and housing characteristics, where we set $\mu(\Lambda) = 0$. This ignores

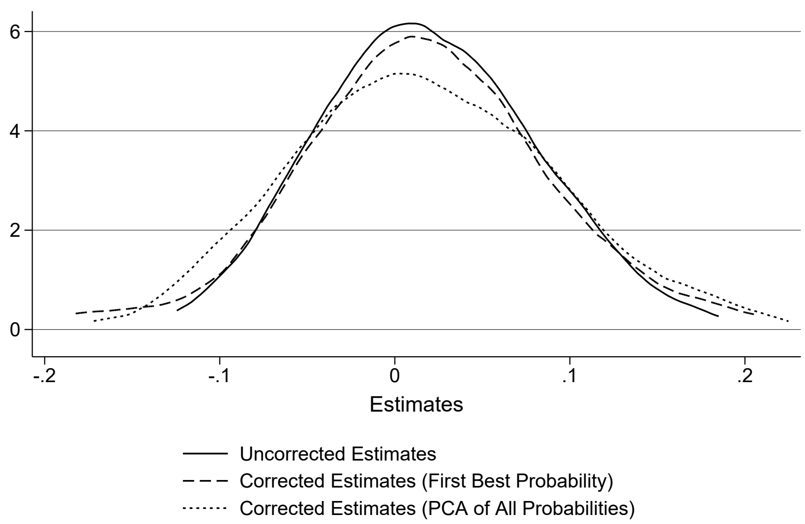
[55]To make this methodology tractable, we need to impose a restriction on the neighborhood choice set. We do so by considering two different choice sets, which lead to similar results. First, we bin clusters into 50 equal groups based on average neighborhood education – individual's choice set is any neighborhood that is in the same group as their current neighborhood quality. Second, we consider all neighborhoods within the same municipality. Below, we report results using the former restriction on the choice set.

selection.

2. A cluster selection approach, where we let $\mu(\Lambda) = \mu(P_k)$, as proposed by Dahl (2002).[56]

3. A cluster selection approach, where $\mu(\Lambda) = \sum_{k=1}^{K} P_k$. In this specification, as opposed to the previous one, we use the whole vector of estimated probabilities to select a given cluster, relaxing the index sufficiency assumption of Dahl (2002). To reduce the dimension of this vector of K probabilities,[57] we conduct a principal component analysis (PCA) and retain the first three principal components.

Figure 7: Distribution of neighborhood-level corrected vs. uncorrected estimates



Notes: Distribution of neighborhood-level corrected vs. uncorrected estimates. Sample includes all parents in Denmark whose children attend 9th grade between 2002 and 2015 and own a property.

The estimated value of β from each of the three approaches are respectively 1.9%, 1.6%, 1.7%. The distributions are shown in Figure 7. These are the percentage increase in house prices for a one standard deviation increase in measured school quality. These estimates are consistent with our previous estimates.

[56] To estimate $\mu()$, we use polynomials of degree 3.

[57] We have about 2,200, which are broken into 50 equal groups. Thus, K is about 44.

8 Conclusion

The Scandinavian welfare state is often regarded as an exemplary system for reducing inequality and equalizing opportunities by providing uniform high quality social services and an education system of uniform high quality that is free for all. Yet, despite equal per capita school expenditure and teacher salaries, there exist substantial differences between schools in terms of quality of teachers and the skill levels of the student peers. These differences are, in part, due to residence-based assignment of students to public schools along with sorting of families and teachers across neighborhoods. More advantaged families sort into neighborhoods where school quality is higher. Equalizing per-pupil expenditure does not equalize school quality.

We provide evidence that access to better schools and neighborhoods through residential choices is capitalized into house prices. Using rich longitudinal administrative data from Denmark, we apply a variety of empirical strategies to estimate the marginal WTP for access to schools in Denmark, where public schools are free. Our estimates show that households are willing to pay around 3% of house prices for a one–standard deviation increase in school test scores. Our results are robust to a variety of specification and robustness checks. In a companion paper (Eshaghnia et al., 2023), we show that our estimate of the willingness to pay for quality is strongly predictive of beneficial child outcomes. Per-pupil expenditures are not the driving force in explaining test scores in Denmark. Parents, peers, and neighbors are more plausible sources of explanatory variation. Disentangling the demands for each of these components is difficult given the high level of inter-correlation among them.

A central conclusion of this paper is that Tiebout-type models of schooling quality in which agents sort by income into neighborhoods to pay for local public goods (school quality) do not apply to Denmark. Our estimates of school quality effects are comparable to those from the US and other countries. It is likely that the estimates for other countries also capture teacher quality and peer effects in neighborhoods and schools and not the school finance effects, stressed in the recent literature. More basic social forces are at work.

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