Pricing Neighborhoods
Appendix*

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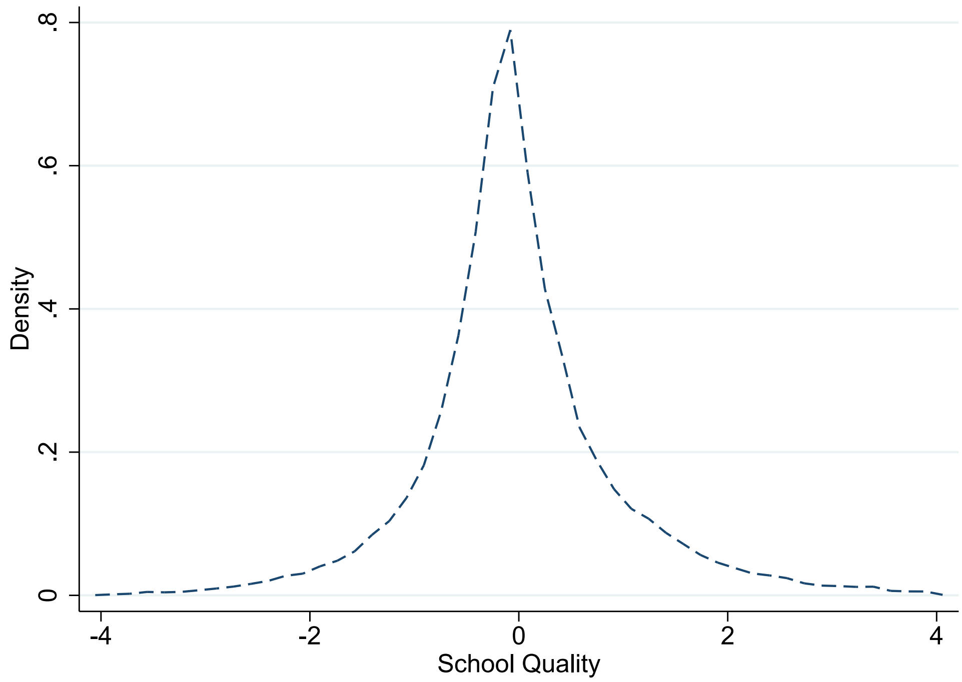
A Data Description

This appendix presents summary statistics of the data we use for the empirical analysis in the paper. Section A.2 documents the correlation between different neighborhood attributes. Section A.3 provides summary statistics on small clusters and details how we expand cluster assignment to the years 2005–2015. Section A.4 provides summary statistics for the control variables.

A.1 Variation in School Quality

In this section, we provide evidence on the variation in our measure of school quality (average test scores). Figure A.1 presents the density of our measure of school quality across schools in Denmark.

Figure A.1: Variation in School Quality



Notes: The figure shows the distribution of school quality (measured as average test scores) in Denmark in 2006.

A.2 Correlation Matrix of Neighborhood Attributes

Table A.1 reports correlations between different neighborhood attributes.

Table A.1: Correlation Between Neighborhood Attributes

	Log Households Gross Income	Households Years of Educ.	Share Criminals	Share Married Households	Share Foreigners	Share non-Westerners
Log Households Gross Income	1					
Households Years of Educ.	0.838***	1				
Share Criminals	-0.196***	-0.207***	1			
Share Married Households	0.662***	0.360***	-0.275***	1		
Share Foreigners	-0.238***	-0.0401***	0.301***	-0.390***	1	
Share non-Westerners	-0.290***	-0.136***	0.304***	-0.337***	0.958***	1
Share Non-Intact Households	-0.316***	-0.217***	0.126***	-0.347***	0.0703***	0.0595***

Notes: This table reports the correlation between the different small cluster level neighborhood attributes we consider in our main strategy. The sample contains all individuals owning a property in Denmark who have a child attending ninth grade in a public school between 2002 and 2006. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

A.3 Characteristics of Clusters

Table A.2 provides summary statistics on clusters.

Table A.2: Summary Statistics of Clusters

	Median	Mean	Std.Dev.
Small Neighborhoods			
Number of Households 2004	245	272.7	115.0
Number of Persons 2004	526	592.2	285.5
Size (in hectares)	22	47.5	64.46
Neighborhoods			
Number of Households 2004	985	1079.7	396.2
Number of Persons 2004	2090	2344.5	1039.0
Size (in hectares)	88	187.9	236.3
# of small neighborhoods	4	4.0	1.3

Note: Summary statistics of the composition of clusters for both neighborhood units. Source: Damm and Schultz-Nielsen (2008).

Since a given address always holds the same cluster ID, we were able to expand the cluster IDs for all individuals (including children), beyond 2004 for addresses that existed before 2004. We do so for 2005 and 2006, achieving a matching rate of 94.4% and 92.5% respectively. However, unique identifiers of addresses changed after 2006, making it more difficult to expand cluster IDs further. We exploit data on a number of housing attributes[1] to conduct probabilistic matching on housing units to recover a unique mapping between housing identifiers across 2006 and 2007. This mapping then allows us to expand our dataset of clusters further from 2007 to 2015, which we use in Appendix D.2, and Sections **??** and **??**.

Given the above challenges, our main estimating sample uses data from 2002 to 2006. In Section D.2, we run our main model separately for each year between 2002 and 2015 and get similar results of the WTP for school quality.

The construction of these clusters ensures that their size remains small, such that we are able to control for unobserved neighborhood-level attributes. However, the requirement that each cluster consists of a minimum number of individuals (150 for

[1]These attributes 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, the age of the property as well as parish code.

small and 600 for clusters), implies that in more rural areas the size of these clusters can remain relatively large. This has two impacts on our empirical strategy. First, the presence of larger clusters reduces our ability to control for unobserved neighborhood level characteristics. Second, we are less likely to have different school catchment areas within each cluster. To avoid such issues, we compute the density (inhabitants per square kilometers) of parishes in which clusters lie as a proxy for clusters' size. We then remove from our sample all observations which lie within the bottom 25th percentile of parishes in terms of density.[2] This reduces our sample by less than 1%, while allowing us to focus on denser areas, where our cluster fixed effects strategy is likely to capture more of the unobserved attributes of the space common to all houses.

A.4 Summary Statistics of Control Variables

This Appendix reports summary statistics on control variables used throughout our analysis.

[2] An alternative strategy would be to remove clusters based on their geographical size. However, as we do not observe the size of clusters in our data, we base our measure on the size of the parishes in which they lie.

Table A.3: Summary Statistics

	Mean	Standard Deviation	Coefficient of Variation
Neighborhood (Cluster) Level – % of Population			
Average Household Gross Income (Excluding Transfers)	52,745	20,200	0.38
Average Household Max. Years of Schooling	12.5	.886	0.07
Fraction of Married Households	.769	.209	0.27
Fraction of Not Intact Households	.506	.232	0.45
Fraction of Foreigners	.050	.083	1.66
Fraction of Non-Western Foreigners	.028	.062	2.21
Fraction of Criminals	.024	.010	2.4
School Level			
Average Household Gross Income (Excluding Transfers)	95,721	23,423	0.25
Average Household Max. Years of Schooling	13.0	.827	0.06
Fraction of Married Households	.768	.097	0.13
Fraction of Not Intact Households	.514	.109	0.21
Fraction of Foreigners	.068	.066	.97
Fraction of Non-Western Foreigners	.030	.049	.1.63
Housing Attributes (Pooled Sample)			
Age of Building (years)	51.0	37.5	0.74
Living Area (square meters)	149.8	47.7	0.32
Number of Floors	1.14	.56	0.49
Number of Apartments	4.19	14.2	3.39
Number of Rooms	5.08	1.45	0.29
Number of Toilets	1.60	.59	0.37
Number of Bathrooms	1.31	.49	0.37
House Price	255,253	218,115	0.86

Notes: This table reports summary statistics on the key variables used in the analyses. Our sample comprises of all Danes who complete ninth grade in years 2002–2006. We focus on homeowners, since we can observe their housing prices. Incomes and house prices are converted from DKK to 2010 USD. An exchange rate of 6.7 DKK per US dollar is used to obtain the dollar values.

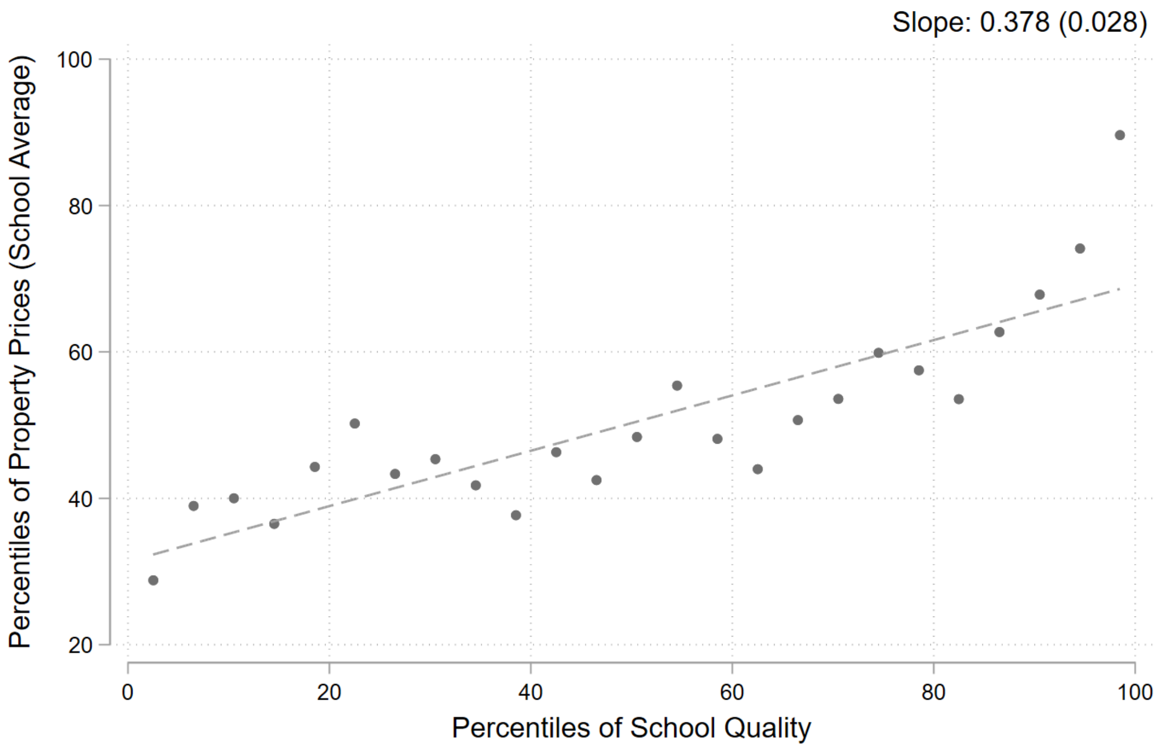
B Sorting

This Appendix presents evidence of the importance of sorting in Denmark, focusing on house prices, individual and neighborhood characteristics, and various measures of school characteristics at different neighborhood units. Section B.1 shows the relationship between house prices and various measures of school characteristics in Denmark as a whole. Section B.2 presents evidence for sorting within clusters. Section B.3 studies the relationship between school attributes, in particular peers, teacher quality, school value-added, and average test score. Section B.4 analyzes the remaining variation in school attributes at difference geographical levels. Finally, Section B.5 presents the correlation between neighborhood and school attributes.

B.1 House Prices and Measured School Quality

Figure B.1 presents the relationship between house prices at the school level and school quality.

Figure B.1: House Prices and School Quality



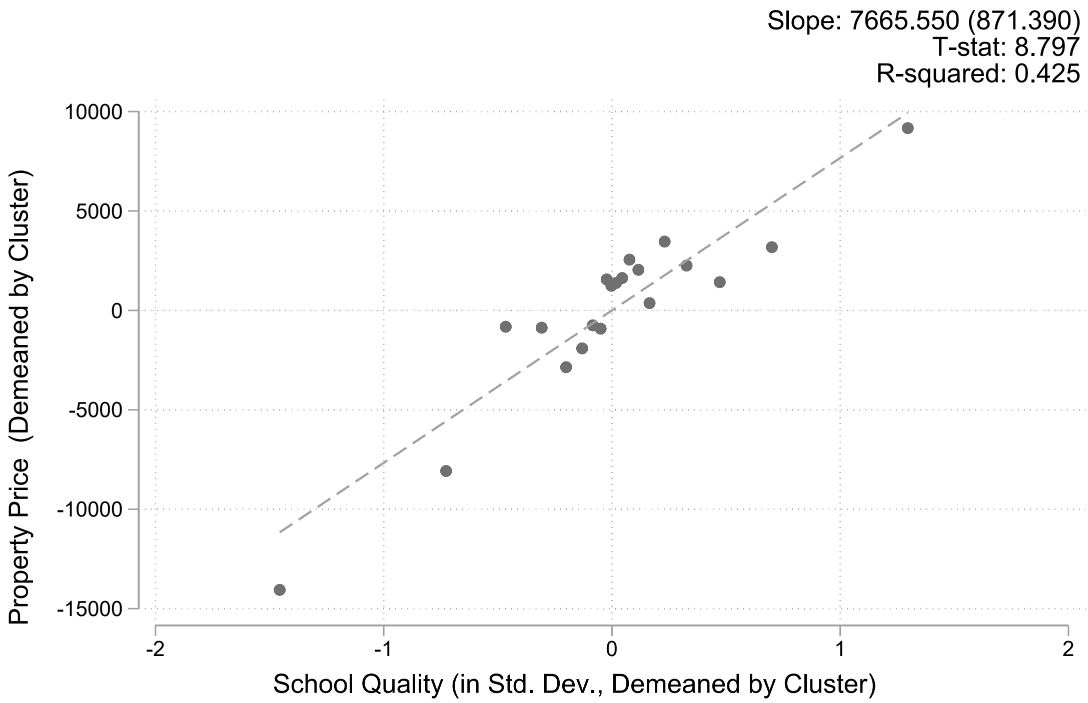
Notes: The figure shows a binned scatter plot (with 20 equal-sized groups), with a linear fit, of percentiles of parental property values averaged at the school level on percentiles of school quality. School quality is measured by taking the average test scores of students attending a given school. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

B.2 Sorting within Clusters

In this section, we present evidence for the sorting of households into schools within clusters. Figure B.2 presents the relationship between house prices averaged at the school level and school quality within clusters. Figure B.3 presents the relationship between a set of housing characteristics and school quality within clusters. Figure B.4 presents the relationship between different individual characteristics and school quality within clusters. Finally, Figures B.5 and B.6 presents the relationship between various neighborhood characteristics and school quality within clusters.

Figure B.2: Sorting Within Clusters - House Price

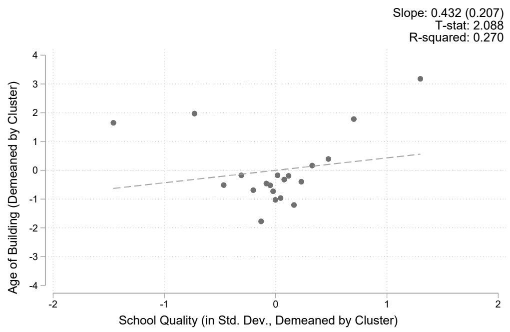
(**a**) Property Price



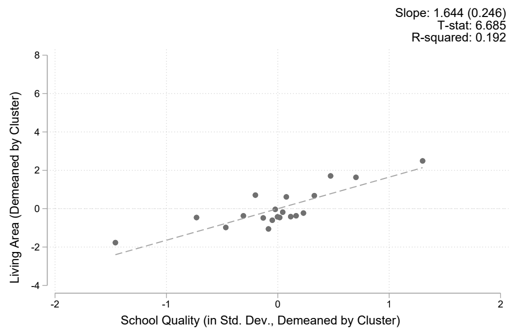
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between house prices and school quality measured by test scores within clusters. This is constructed by regressing property prices on school quality, controlling for neighborhood-by-cohort fixed 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. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

Figure B.3: Sorting within Clusters (Housing Characteristics)

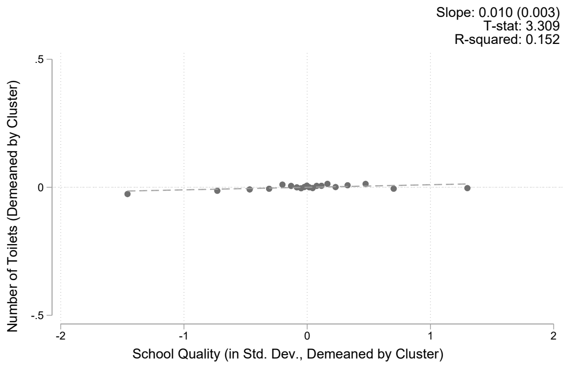
(**a**) Building Age



(**b**) Living Area



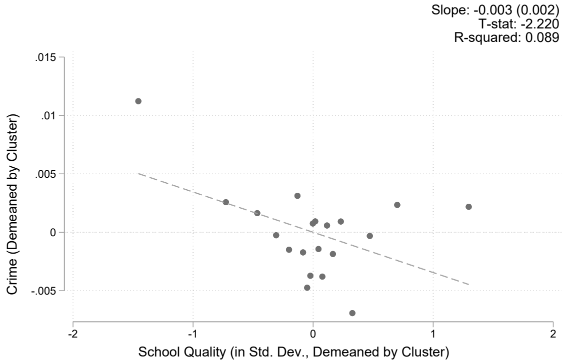
(**c**) Number of Toilets



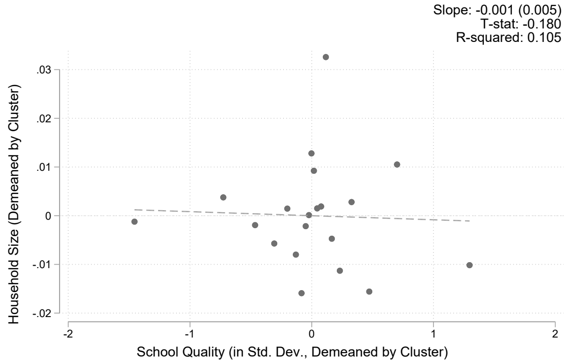
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between housing characteristics and school quality measured by test scores within clusters. This panel is constructed by regressing various housing attributes on school quality, controlling for neighborhood-by-cohort 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. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

Figure B.4: Sorting within Clusters (Individual Characteristics)

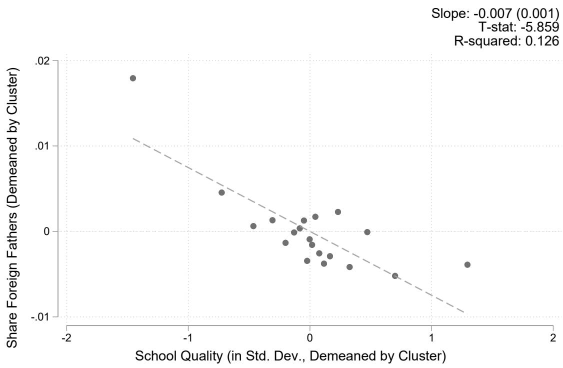
(**a**) Ever Committed a Crime



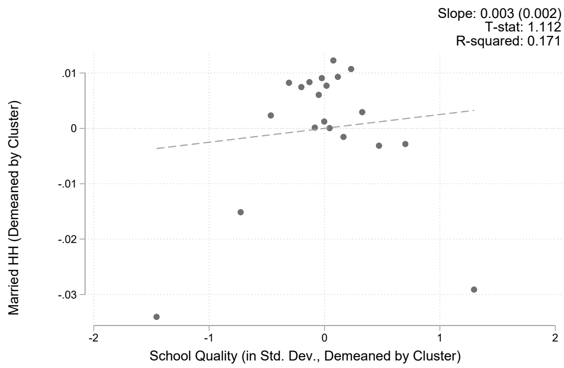
(**b**) Household Size



(**c**) Foreign Father



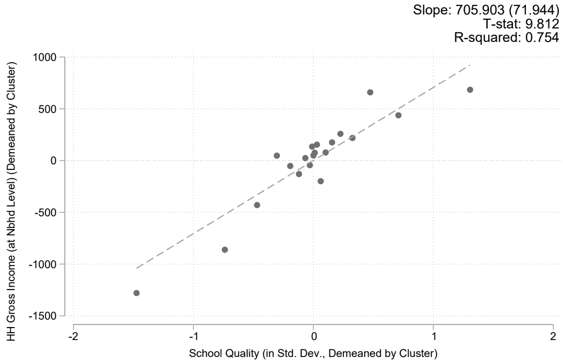
(**d**) Married Household



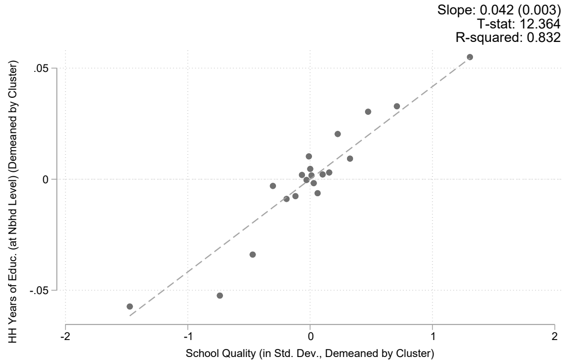
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between individual characteristics and school quality measured by test scores within clusters. Each panel is constructed by regressing various individual characteristics on school quality, controlling 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. To measure crime, we use an indicator for whether parents ever committed a crime or not. We exclude traffic-related crimes. Standard errors corrected for clustering at the cluster-cohort level are reported in the top right corner. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

Figure B.5: Sorting within Clusters (Neighborhood Characteristics)

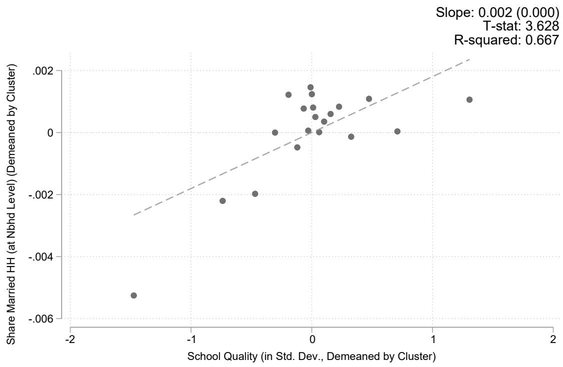
(**a**) Neighborhood Average Income



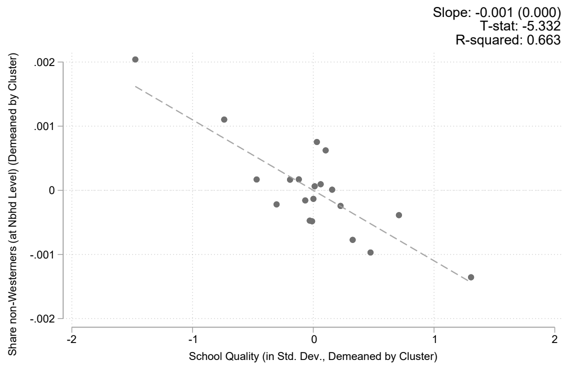
(**b**) Neighborhood Average Education



(**c**) Neighborhood Share of Married Households



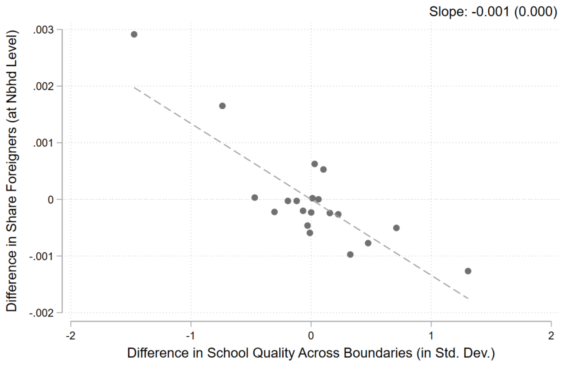
(**d**) Neighborhood Share of Non-Western Foreigners



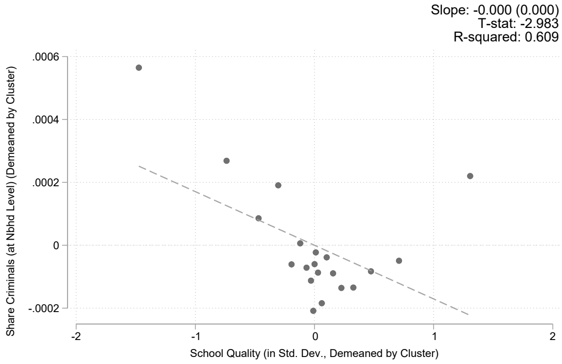
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between neighborhood characteristics and school quality measured by test scores within clusters. Each panel is constructed by regressing various small cluster characteristics on school quality, controlling for neighborhood-by-cohort fixed effects and 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. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

Figure B.6: Sorting within Clusters (Neighborhood Characteristics)- Origin, Crime, and Family Structure

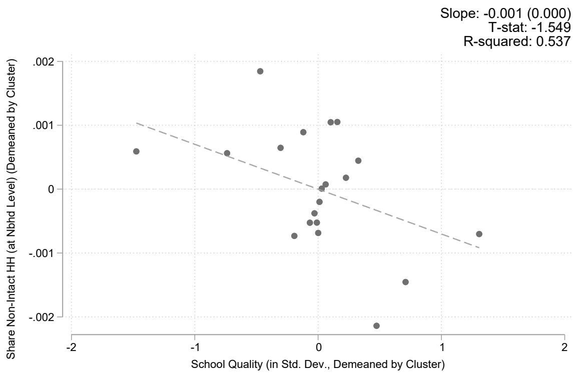
(**a**) Neighborhood Share of Foreigners



(**b**) Neighborhood Share of Criminals



(**c**) Neighborhood Share of Non-Intact Households



Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between neighborhood characteristics and school quality measured by test scores within clusters. Each panel is constructed by regressing various small cluster characteristics on school quality, controlling for neighborhood-by-cohort fixed effects and 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. The sample contains property values for parents who have a child attending ninth grade in a public school between 2002 and 2006.

B.3 Relationship among Different Measures of Quality

Our objective in this Appendix is to clarify our use of school average test scores as measures of school quality. The evidence below points to strong correlations among various school inputs, school value-added and school average test score. In light of such strong correlations it is not possible to precisely estimate the separate effects of different school inputs in samples at our disposal.

In Section B.3, we look at two sets of inputs entering the school production function, namely teacher quality and peer quality and relate them to school average test score. The construction of these variables is briefly presented in Section B.3.1. We show how these variables are strongly correlated. These figures also provide further evidence on the sorting process in Denmark within neighborhoods.

B.3.1 Data

The main sample used in this paper consists of cohorts in school between 2002 and 2006 who complete 9th grade. The analysis in this Appendix uses cohorts between 2002 and 2015, due to the following considerations. First, data on teacher quality is available from 2008 onward. Second, 8th grade test scores, which are used to construct school value-added estimates are available from 2011 onward.

We note that the literature has studied the role of observed teacher quality characteristics on outcomes (see for instance Rivkin et al. (2005)), while stressing that unobservables tend to play a much more significant role in explaining the impact of teachers in influencing children's later life outcomes.

In the sections below, we look at the following peer quality variables, which we average over all students attending a given school:

- Average household gross income excluding transfers;
- Maximum household education;
- Non-western origin of the child.

In terms of teacher quality, we focus on the following observed characteristics:

- Teacher GPA rank at teacher's college;
- Teacher age when graduating from teacher's college;
- Teacher tenure (only observed up to 3 years in a given school);
- Teacher quality index.[3]

Finally, we construct a measure of school value-added, following the methodology of Chetty et al. (2014) applied to schools. We control for 8th grade test scores, and a vector of household characteristics, including parental income, wealth, education, criminal record and marital status, as well as child order and gender.

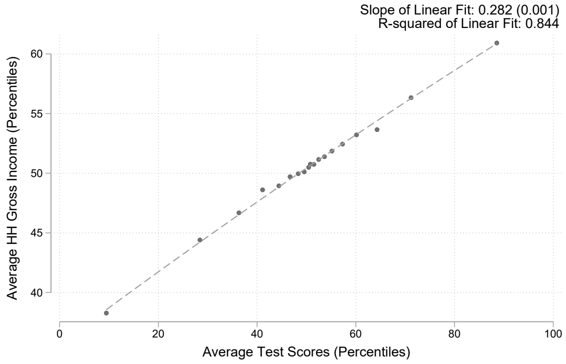
This section provides evidence on the relationship between various school attributes, as well as an output of the school production function, namely school average test score. All the variables used in analysis below in Section B.3 are ranked between 0 and 100.

Figures B.7-B.10 provide suggestive evidence of the strong correlation between these different inputs which enter the school quality production function and the output, namely test scores. Given such correlations, estimating the separate effects of each of these components is difficult.

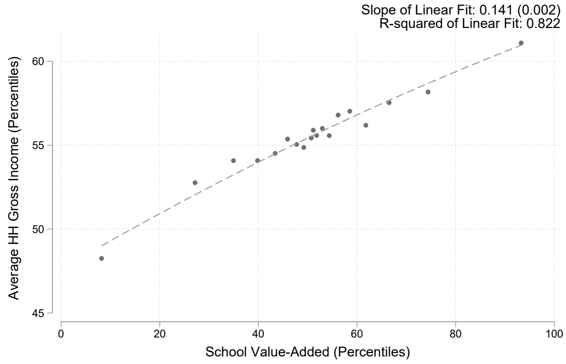
[3] As described in Section **??**, the teacher quality index is constructed as follows. Using administrative records, all employees in teaching positions in schools between 2009 and 2016 are matched to their (a) academic records from high school (grades in Danish and Mathematics exams) and university 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. This index is based on Gensowski et al. (2021).

Figure B.7: Correlations Between Percentile of Household Average Gross Income at School Level and School Characteristics (As Specified in Sub-figure Title)

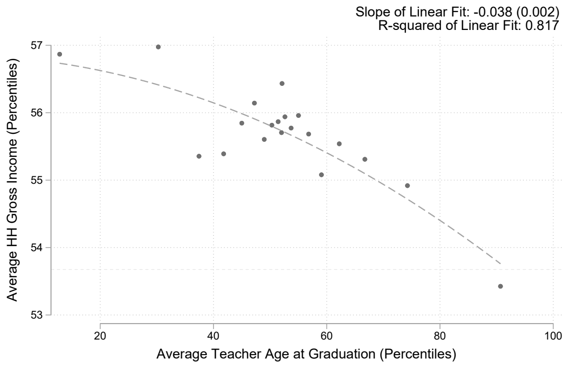
(**a**) School Average Test Scores



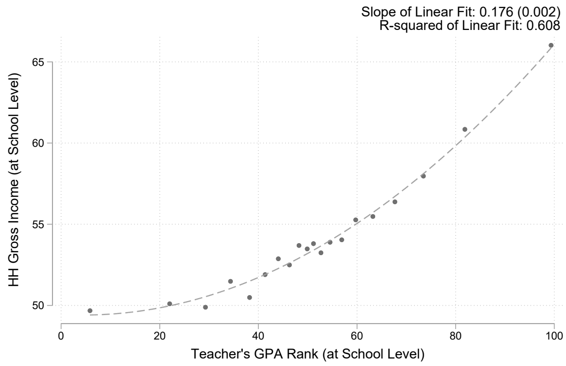
(**b**) School Value-Added



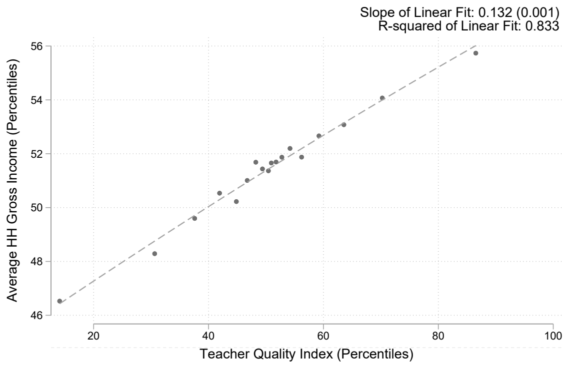
(**c**) Average Age at Graduation of Teachers



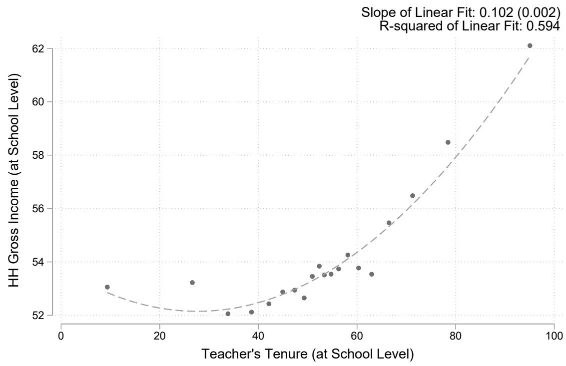
(**d**) Average Teacher GPA Rank at Teacher's College



(**e**) Teacher Quality Index



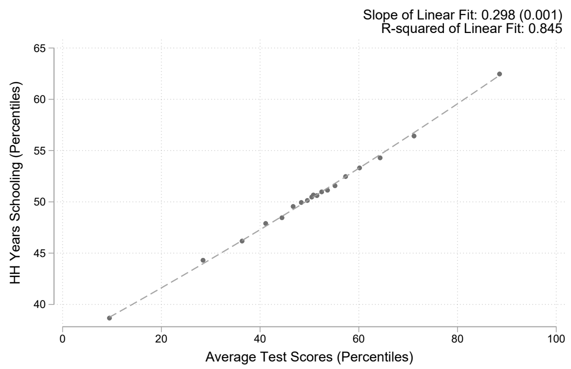
(**f**) Average Teacher Tenure



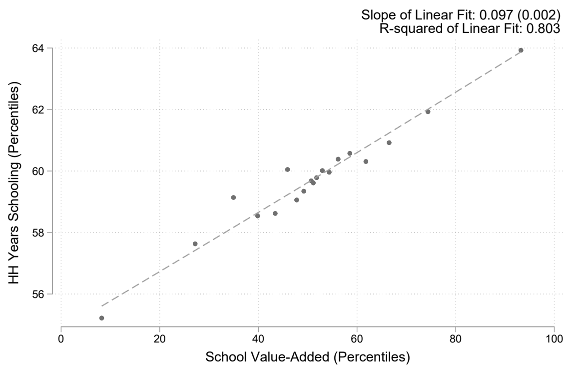
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting the relationship between school-level average household gross income, school inputs and our measure of school quality (measured by average test scores). These figures control for neighborhood-by-cohort fixed effects. All variables are transformed into percentiles.

Figure B.8: Correlations Between Percentile of Household Years of Education at School Level and School Characteristics (As Specified in Sub-figure Title)

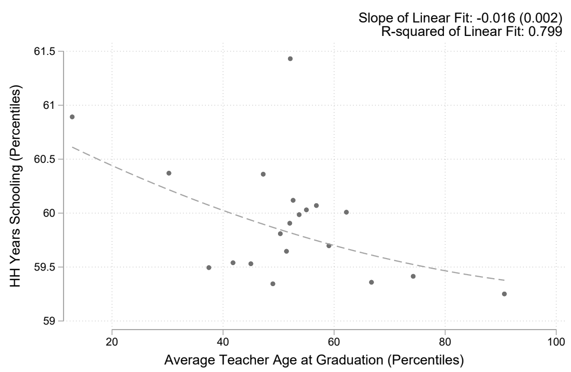
(**a**) School Average Test Scores



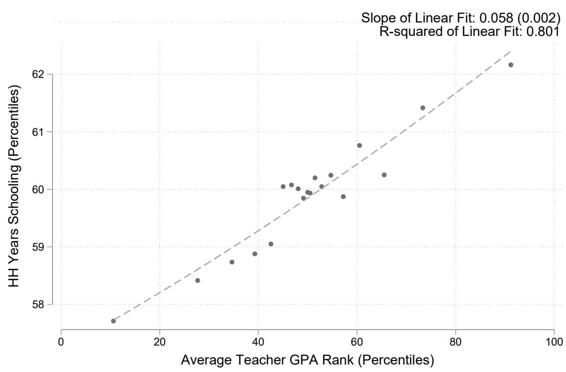
(**b**) School Value-Added



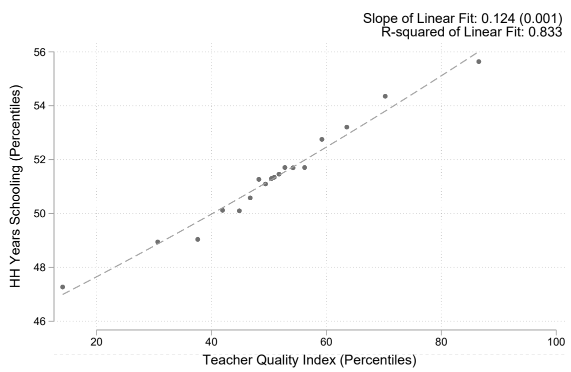
(**c**) Average Age at Graduation of Teachers



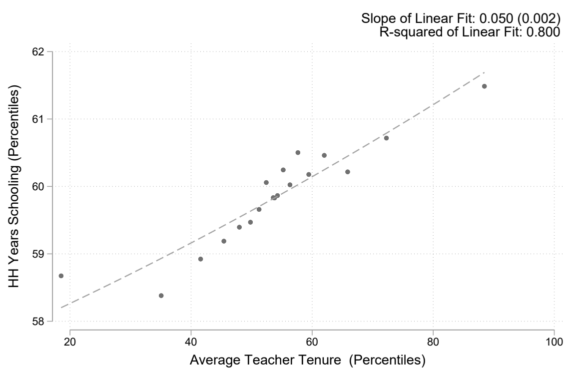
(**d**) Average Teacher GPA Rank at Teacher's College



(**e**) Teacher Quality Index



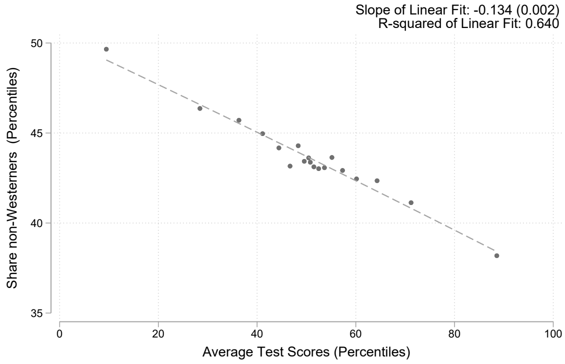
(**f**) Average Teacher Tenure



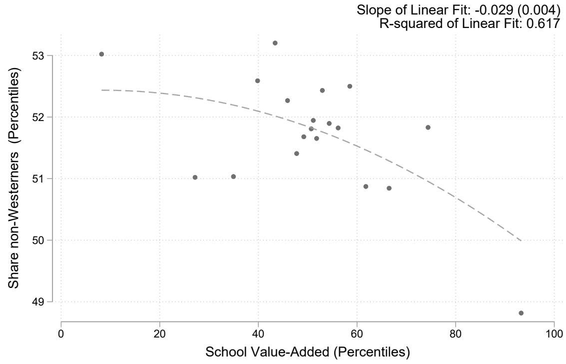
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting relationship between school-level maximum parental years education, school inputs and our measure of school quality (measured by average test scores). These figures control for neighborhood-by-cohort fixed effects. All variables are transformed into percentiles.

Figure B.9: Correlations Between Percentile of Share of Non-Westerners at School Level and School Characteristics (As Specified in Sub-figure Title)

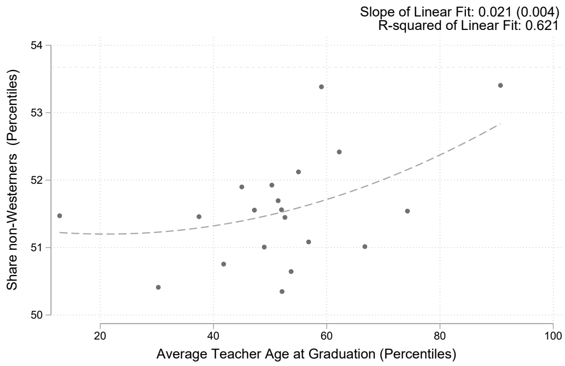
(**a**) School Average Test Scores



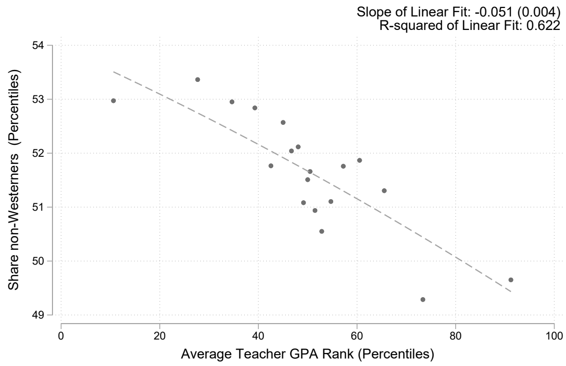
(**b**) School Value-Added



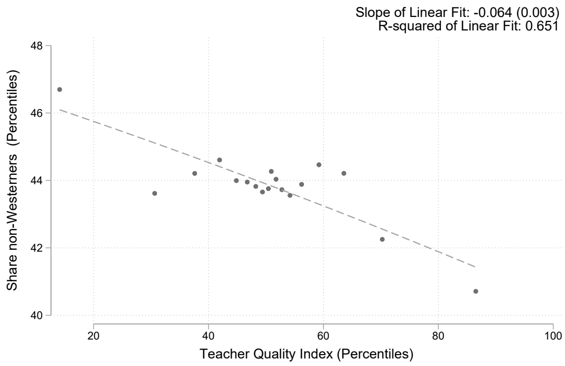
(**c**) Average Age at Graduation of Teachers



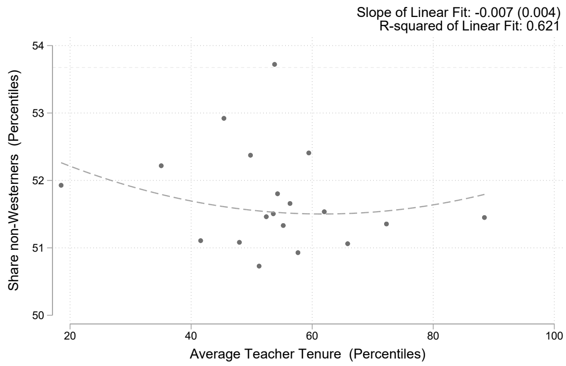
(**d**) Average Teacher GPA Rank at Teacher's College



(**e**) Teacher Quality Index



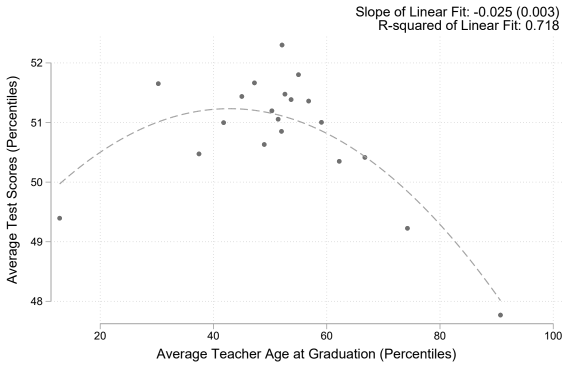
(**f**) Average Teacher Tenure



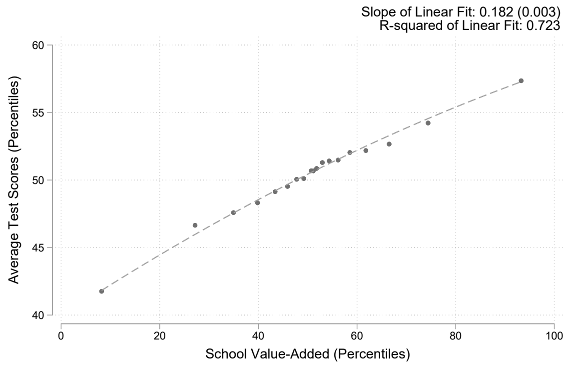
Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting relationship between school-level share of non-westerner, school inputs and our measure of school quality (measured by average test scores). These figures control for neighborhood-by-cohort fixed effects. All variables are transformed into percentiles.

Figure B.10: Correlations Between Percentile of School Average Test Scores and School Characteristics (As Specified in Sub-figure Title)

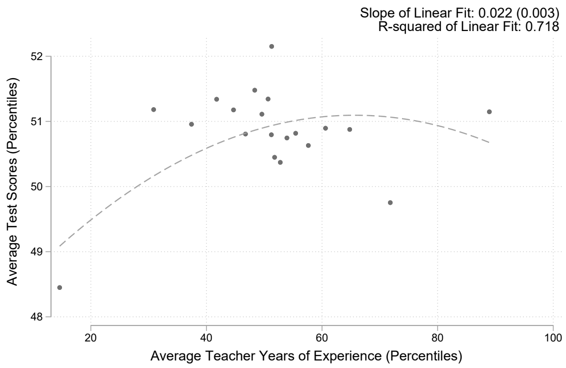
(**a**) Average Age at Graduation of Teachers



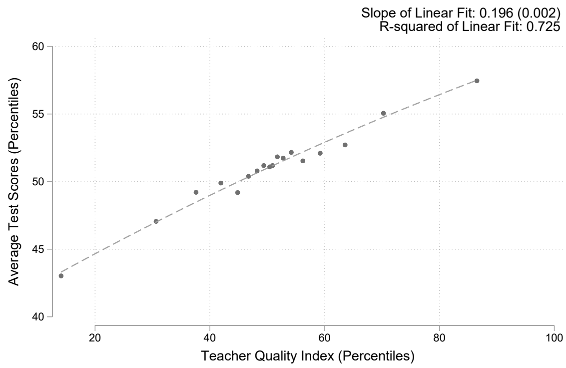
(**b**) School Value-Added



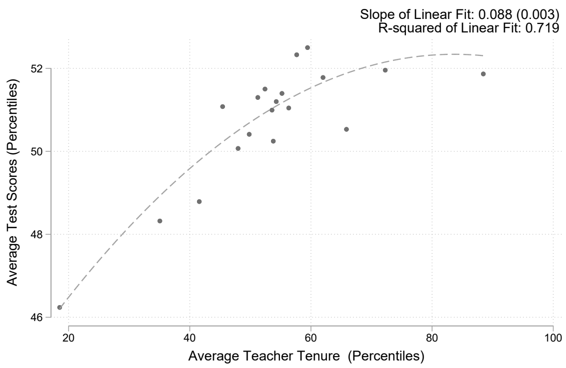
(**c**) Average Years of Experience of Teachers



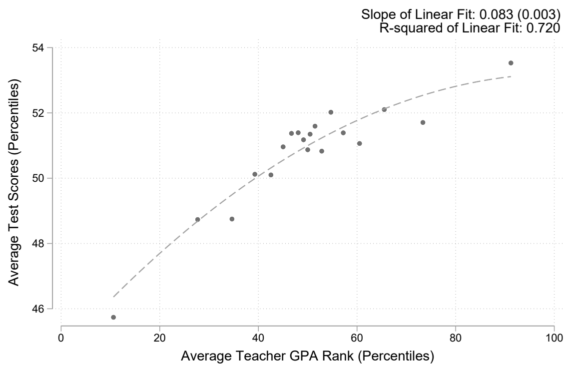
(**d**) Teacher Quality Index



(**e**) Average Teacher Tenure



(**f**) Average Teacher GPA Rank at Teacher's College

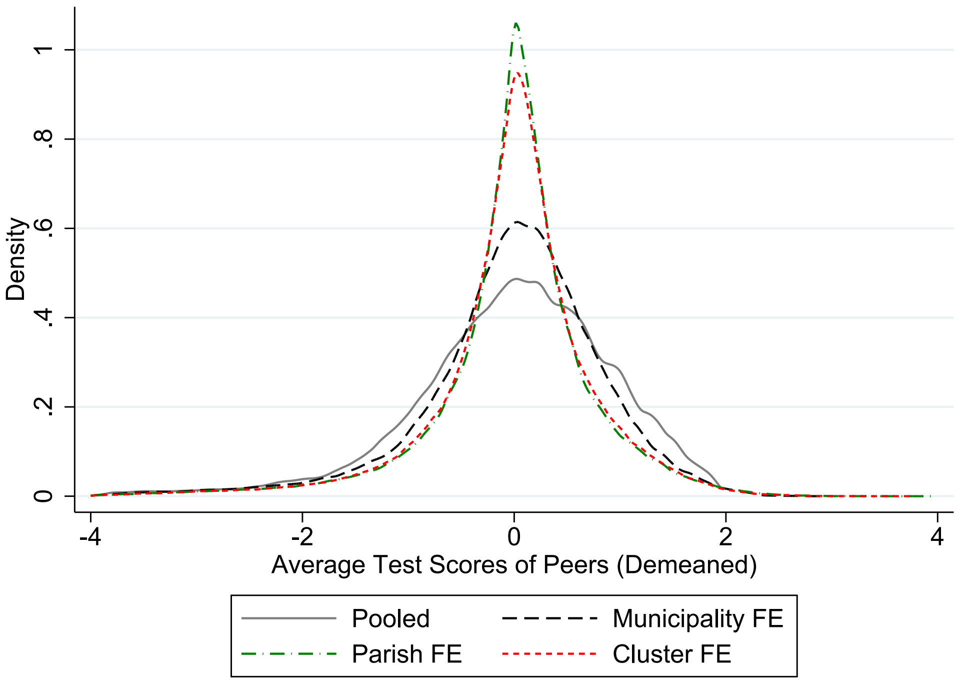


Notes: This figure presents a binned scatter plot (with 20 equal-sized groups) depicting relationship between school-level average test scores (our measure of "School Quality") and school inputs. These figures control for neighborhood-by-cohort fixed effects. All variables are transformed into percentiles.

B.4 Variation in School Attributes

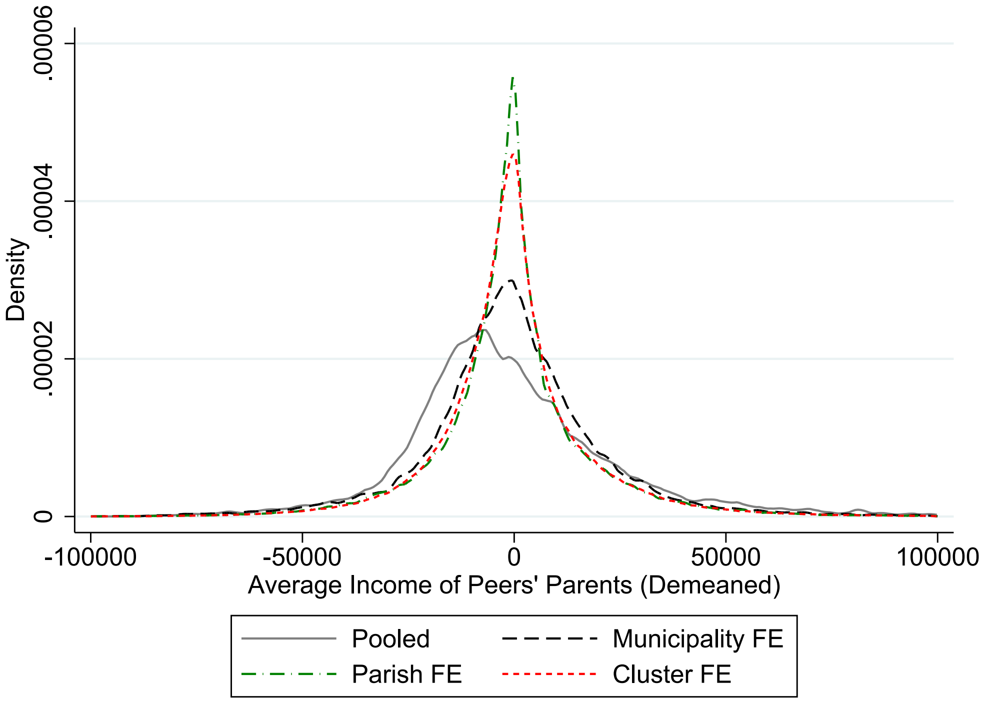
This section provides evidence on the variation in school attributes and average school test scores at different geographical levels in Denmark. By plotting these densities after controlling for fixed effects at various geographical levels, this section documents the important level of sorting of household in various attributes. Figures B.11-B.15 present the results. Table B.1 reports the corresponding variance of each of the school attributes in Figures B.11-B.15 at different geographical levels.

Figure B.11: Density of School's Average Test Scores by Geographical Level



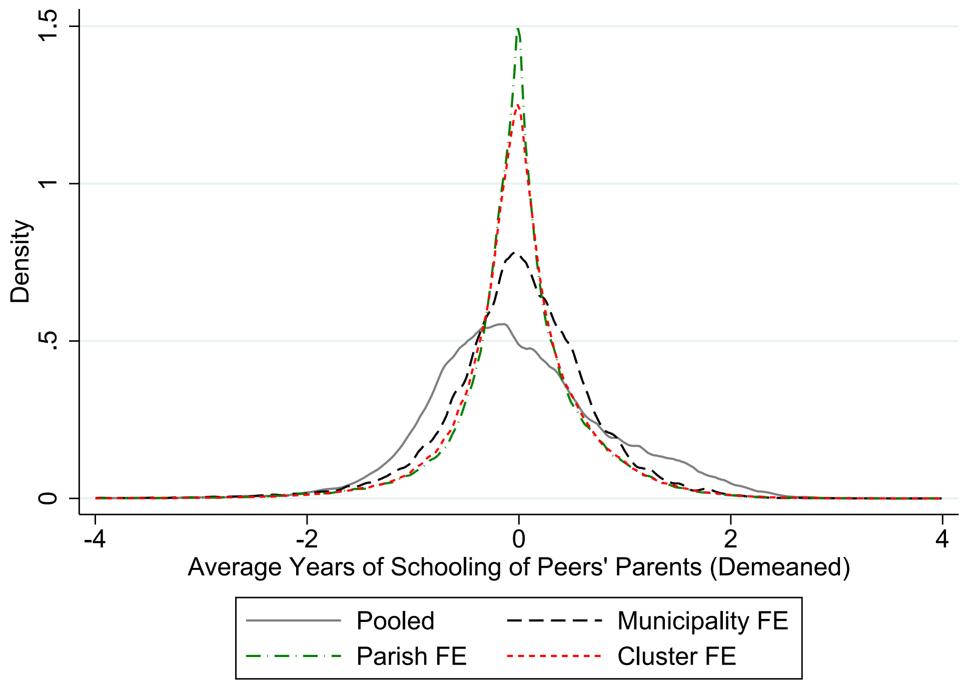
Notes: The figure shows the distribution of the school-level average of test scores at different geographical levels in Denmark. The solid line shows the distribution for the whole country after taking out school-by-year fixed effects. The dashed line presents the distribution after taking out school-by-municipality fixed-effects. The dash-dot line shows the distribution after taking out school-by-parish fixed-effects. Finally, the dot line presents the distribution after taking out school-by-cluster fixed-effects. The corresponding standard deviations are 0.92, 0.84, 0.75, and 0.75, respectively for the pooled, municipality FE, parish FE, and cluster FE.

Figure B.12: Density of School's Average Parental Income by Geographical Level



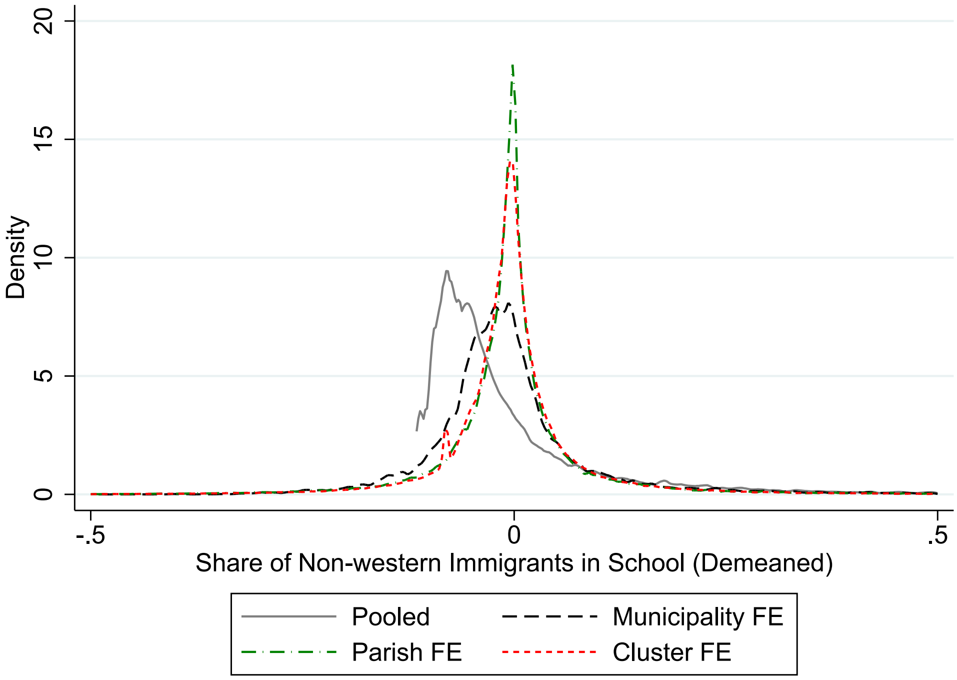
Notes: The figure shows the distribution of the school-level average of parental income of students at different geographical levels in Denmark. The solid line shows the distribution for the whole country after taking out school-by-year fixed effects. The dashed line presents the distribution after taking out school-by-municipality fixed-effects. The dash-dot line shows the distribution after taking out school-by-parish fixed-effects. Finally, the dot line presents the distribution after taking out school-by-cluster fixed-effects. The corresponding standard deviations are about 20300, 19000, 17000, and 16100, respectively for the pooled, municipality FE, parish FE, and cluster FE.

Figure B.13: Density of School's Average Parental Education Level by Geographical Level



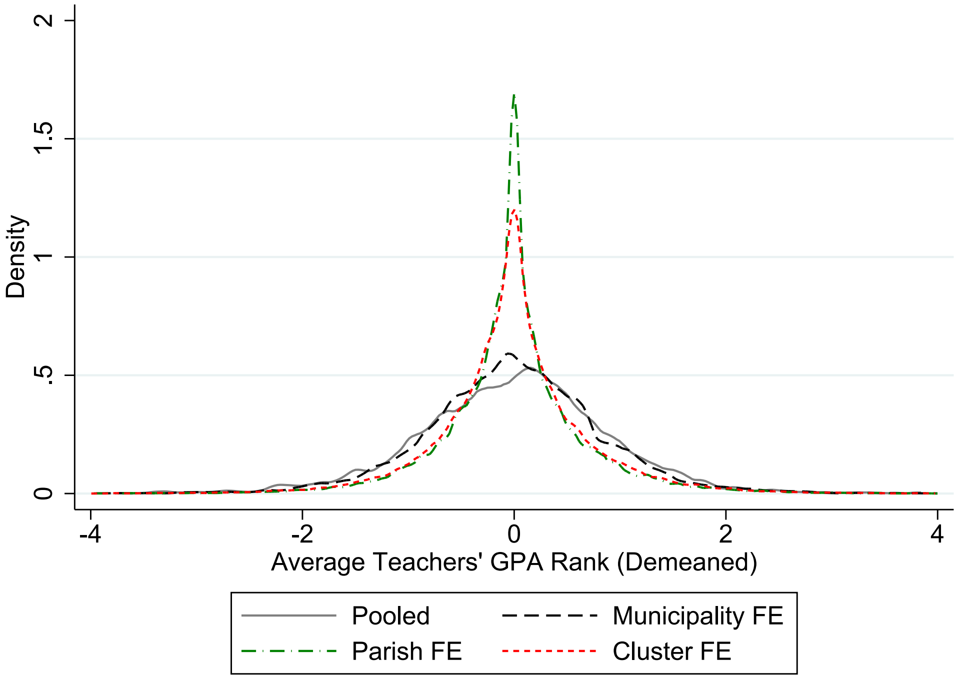
Notes: The figure shows the distribution of the school-level average of students' parental years of formal schooling at different geographical levels in Denmark. The solid line shows the distribution for the whole country after taking out school-by-year fixed effects. The dashed line presents the distribution after taking out school-by-municipality fixed-effects. The dash-dot line shows the distribution after taking out school-by-parish fixed-effects. Finally, the dot line presents the distribution after taking out school-by-cluster fixed-effects. The corresponding standard deviations are about 0.84, 0.67, 0.58, and 0.58, respectively for the pooled, municipality FE, parish FE, and cluster FE.

Figure B.14: Density of Share of Immigrants in School by Geographical Level



Notes: The figure shows the distribution of the school-level share of students who are non-western immigrants, at different geographical levels in Denmark. The solid line shows the distribution for the whole country after taking out school-by-year fixed effects. The dashed line presents the distribution after taking out school-by-municipality fixed-effects. The dash-dot line shows the distribution after taking out school-by-parish fixed-effects. Finally, the dot line presents the distribution after taking out school-by-cluster fixed-effects. The corresponding standard deviations are about 0.098, 0.087, 0.077, and 0.076, respectively for the pooled, municipality FE, parish FE, and cluster FE.

Figure B.15: Density of School's Average Quality of Teachers (Teachers' GPA Ranks) by Geographical Level



Notes: The figure shows the distribution of the school-level average of teachers' quality measures by teachers' GPA rank in college, at different geographical levels in Denmark. The solid line shows the distribution for the whole country after taking out school-by-year fixed effects. The dashed line presents the distribution after taking out school-by-municipality fixed-effects. The dash-dot line shows the distribution after taking out school-by-parish fixed-effects. Finally, the dot line presents the distribution after taking out school-by-cluster fixed-effects. The corresponding standard deviations are about 0.89, 0.83, 0.67, and 0.70, respectively for the pooled, municipality FE, parish FE, and cluster FE.

Table B.1: Variance of School Attributes at Different Geographical Levels

	Pooled	Municipality	Parish	Cluster
Variance of School's Average Test scores	0.85	0.71	0.56	0.56
Variance of School's Average Parental Income	$412 * 10^6$	$361 * 10^6$	$289 * 10^6$	$260 * 10^6$
Variance of School's Average Parental Years of Schooling	0.71	0.45	0.34	0.34
Variance of Share of Non-western Immigrants	0.010	0.008	0.006	0.0005
Variance of School's Average Teachers' GPA Rank	0.89	0.83	0.67	0.70

Notes: This table reports the variance of different school characteristics in our analysis sample at various geographic levels, presented in Figures B.11-B.15. Incomes are converted from DKK to 2010 USD. An exchange rate of 6.7 DKK per US dollar is used to obtain the dollar values.

B.5 Correlation between different school and neighborhood characteristics

Table B.2 presents the correlation between different school characteristics. Table B.3 shows the correlation between various teachers' characteristics (averaged at school level) and other school characteristics such as average test scores and parental education level.

The correlation between school characteristics (test scores, characteristics of peers' family, and teachers' characteristics) across years are high ranging from 0.6 to 0.8 over the studied years.

Table B.2: Correlation Between School Characteristics

	Avg Log HH Gross Income	Avg Parental Years of Educ.	Avg Test Scores	Share of Criminal Parents	Share Married HH	Share Foreigners	Share non-Westerners
Avg Parental Log HH Gross Income	1						
Avg Parental Years of Educ.	0.72***	1					
Avg Test Scores	0.61***	0.62***	1				
Share of Criminal Parents	-0.07***	-0.04***	-0.07***	1			
Share Married Households	0.23***	0.17***	0.40***	-0.07***	1		
Share Foreigners	-0.40***	-0.09***	-0.29***	0.05***	-0.22***	1	
Share non-Westerners	-0.46***	-0.14***	-0.29***	0.04***	-0.10***	0.91***	1
Share Non-Intact Households	-0.06***	-0.04***	-0.21***	0.03***	-0.57***	0.05***	-0.03***

Notes: This table reports the correlation between the different school characteristics in our analysis sample. We use an indicator for whether any individual in a given neighborhood ever committed a crime or not. We exclude traffic-related crimes. Parental incomes are measured in 2010 USD. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B.3: Correlation Between Average Teachers' Characteristics at School Level and Average Test Scores at School Level

	Avg Test Scores	Avg Teachers' GPA Rank	Avg Teachers' Tenure	Avg Teachers' Experience	Avg Teachers' Age at Grad.
Avg Test Scores	1				
Avg Teachers' GPA Rank	0.20***	1			
Avg Teachers' Tenure	0.13***	0.06***	1		
Avg Teachers' Experience	-0.04***	-0.05***	0.25***	1	
Avg Teachers' Age at Graduation	-0.05***	-0.04***	0.05***	-0.18***	1
Avg Parental Years of Educ.	0.62***	0.22***	0.03***	-0.18***	0.01***

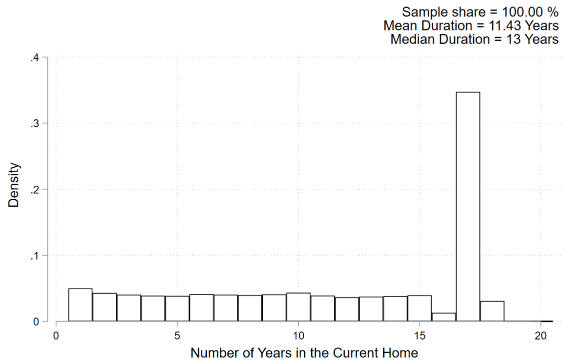
Notes: This table reports the correlation between the different school characteristics in our analysis sample. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

C Number of Years Spent in Current House

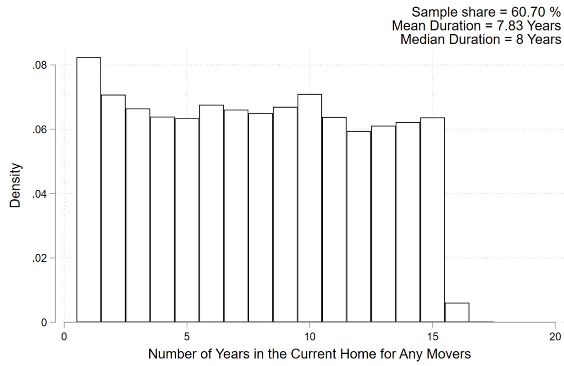
This section provides evidence that, on average, children who complete 9th grade in Denmark live for a significant number of years in the same residence. In the series of figures below, we show the number of years spent by these student in their last recorded home at grade 9, conditional on the number of moves they have experienced in their life. We show how a significant share of these students never moved (close to 40%) while a similar fraction (around 30%) moved only once.

Figure C.1: Number of Years Spent in Current Home

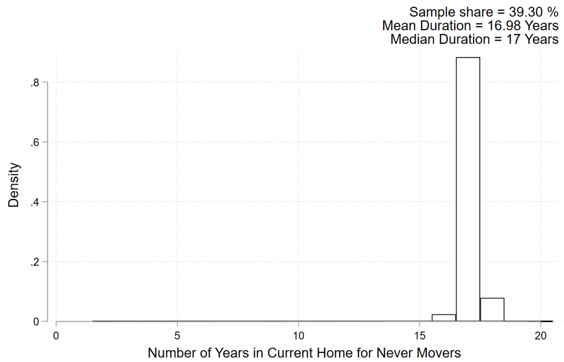
(**a**) Whole Sample



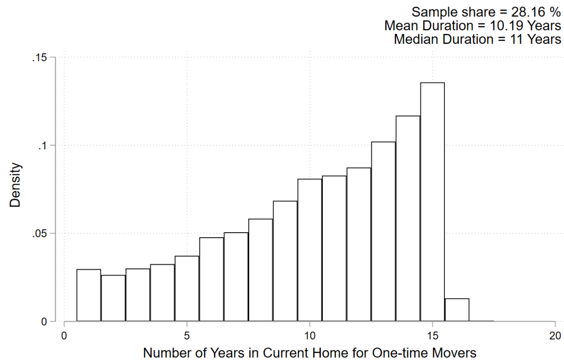
(**b**) Movers



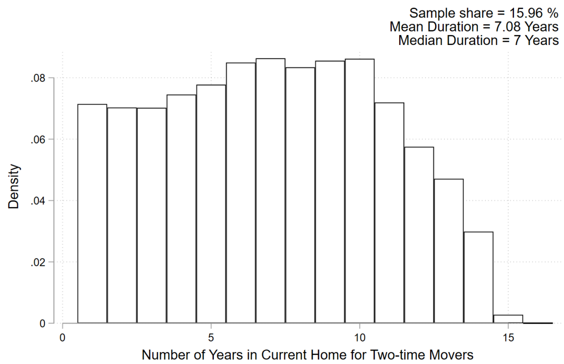
(**c**) Never Movers



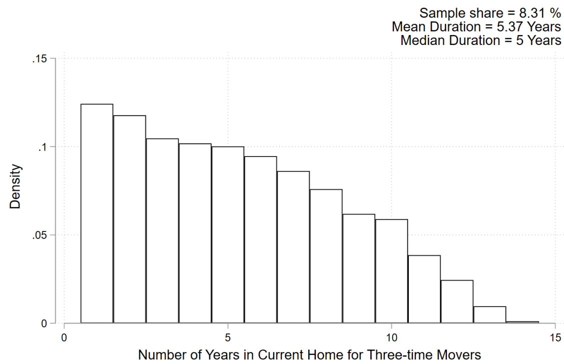
(**d**) One-time Movers



(**e**) Two-time Movers



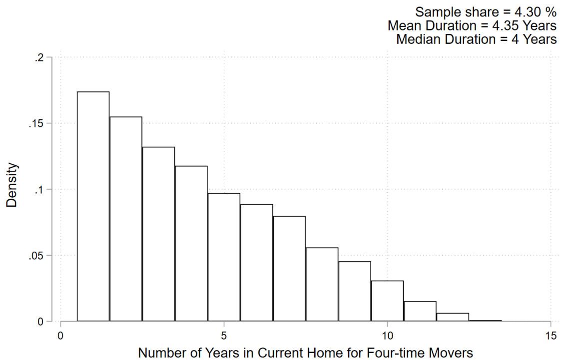
(**f**) Three-time Movers



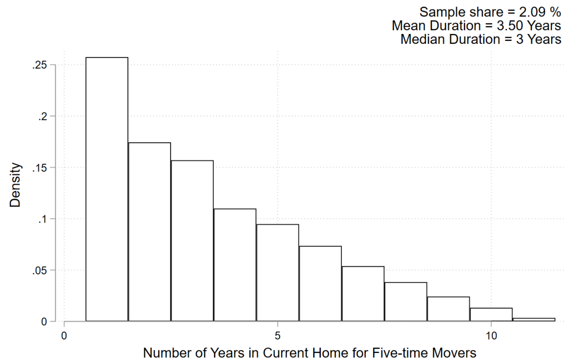
Note: Figures show densities for the number of years children spend in the same home as the one observed during ninth grade, conditional on a given number of moves since age 0. The sample shares, mean and median duration are provided in the upper right corner of each subfigures.

Figure C.2: Number of Years Spent in Home

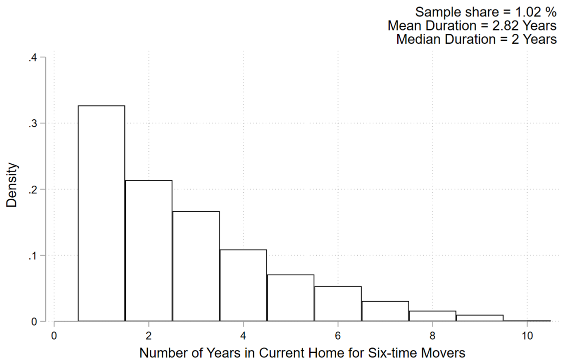
(**a**) Four-time Movers



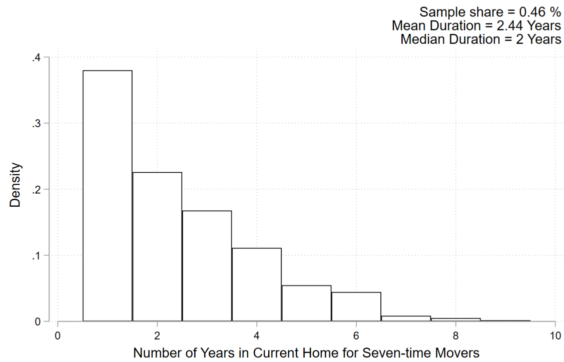
(**b**) Five-time Movers



(**c**) Six-time Movers



(**d**) Seven-time Movers



Note: Figures show densities for the number of years children spend in the same home as the one observed during ninth grade, conditional on a given number of moves since age 0. The sample shares, mean and median duration are provided in the upper right corner of each subfigures

D Estimation Approaches: BDD and Temporal Shocks

D.1 Boundary Discontinuity Design

Black (1999) uses a boundary discontinuity design (BDD) to address the endogeneity issue. She uses a regression discontinuity design (RDD) approach that is based on boundary fixed effects in order to compare houses that are near but on opposite sides of school catchment area borders. The identifying assumption for that approach is that unobserved amenities vary continuously at the border while school characteristics are determined by attendance zones that are discontinuous at boundaries. Estimates using this approach are typically five times smaller than cross-sectional estimates (see Bayer et al., 2007; Gibbons et al., 2013).

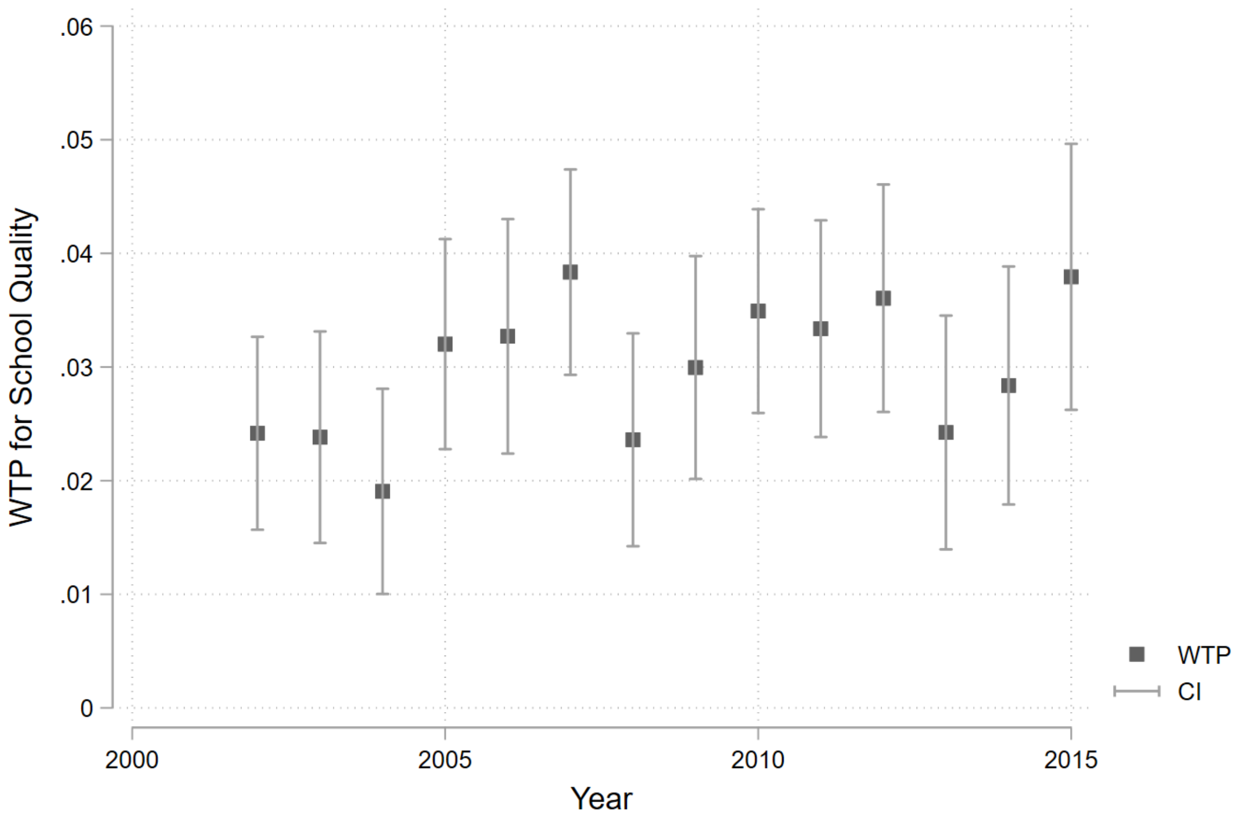
BDD approaches have been used that exploit changes in boundaries (see, for instance, Bogart and Cromwell, 2000 and Ries and Somerville, 2010). Those studies lack information on both neighborhood quality and school characteristics. Moreover, variation can arise from houses that are geographically distant from each other, albeit close to the boundary (and thus in different types of neighborhoods). Finally, BDD designs rely on variation at the boundary, which, without further evidence, may not be representative of the broader population. Our approach using cluster fixed effects, by construction, is not subject to these issues.

D.2 Using Temporal Shocks

An important drawback to methods that use temporal shocks to school quality, such as difference-in-difference approaches, to derive WTP estimates is exposited by Kuminoff and Pope (2014). Their work shows that these studies need to assume (and do so without providing evidence) that the hedonic price function is constant over periods of years (sometimes decades). Our main strategy does not require this assumption.

Our empirical strategy allows us to provide a test of this assumption. Figure D.1 presents the WTP estimates over the years 2002–2015. To go beyond our estimation sample used in the main paper (2002 to 2006), we expand the mapping of housing units to clusters as explained in Appendix A.3 through probabilistic matching. We fail to reject the null hypothesis that the WTP over the studied years are not statistically different from each other using an F-test with a p-value of 0.56.

Figure D.1: WTP for School Quality by Cohorts



Notes: This figure shows the WTP for school quality for different cohorts between 2002 to 2015. Sample includes all parents in Denmark whose children attend ninth grade in public schools between 2002 and 2015 and own a property. 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. 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

E Spatial Decomposition of Inequality

In this appendix, we study inequality within neighborhood units in Denmark. The Theil's T decomposition is computed as follows.[4] Consider the population of Danish households, $i = 1, ..., n$, with income y_i, and weight w_i. Let $f_i = w_i/N$, where $N = \sum w_i$. When the data are unweighted, $w_i = 1$ and $N = n$. Arithmetic mean income is m. Now, consider the exhaustive partition of the population into mutually-exclusive neighborhoods $k = 1, ..., K$. The Generalized Entropy class of inequality indices across neighborhoods is given by:

$$GE(a) = \frac{1}{a(a-1)}[\sum f_i(\frac{y_i}{m}^a) - 1], a \neq 0 \ \& \ a \neq 1,$$

$$T_t = GE(1) = \sum f_i \frac{y_i}{m} \log \frac{y_i}{m},$$

$$GE(0) = \sum f_i \log \frac{y_i}{m},$$

$GE(a)$ index can be decomposed as

$$GE(a) = GE_W(a) + GE_B(a)$$

where $GE_W(a)$ is within-group inequality and $GE_B(a)$ is between-group inequality and

$$GE_W(a) = \sum v_k^{1-a} s_k^a GE_k(a),$$

which, for Theil's T index is as follows:

$$GE_W(1) = \sum s_k GE_k(1)$$

where $v_k = \frac{N_k}{N}$ is the number of persons in subgroup k divided by the total number of persons (subgroup population share), and s_k is the share of total income held by k's members (subgroup income share), i.e., v_k is the sum of the weights in subgroup k

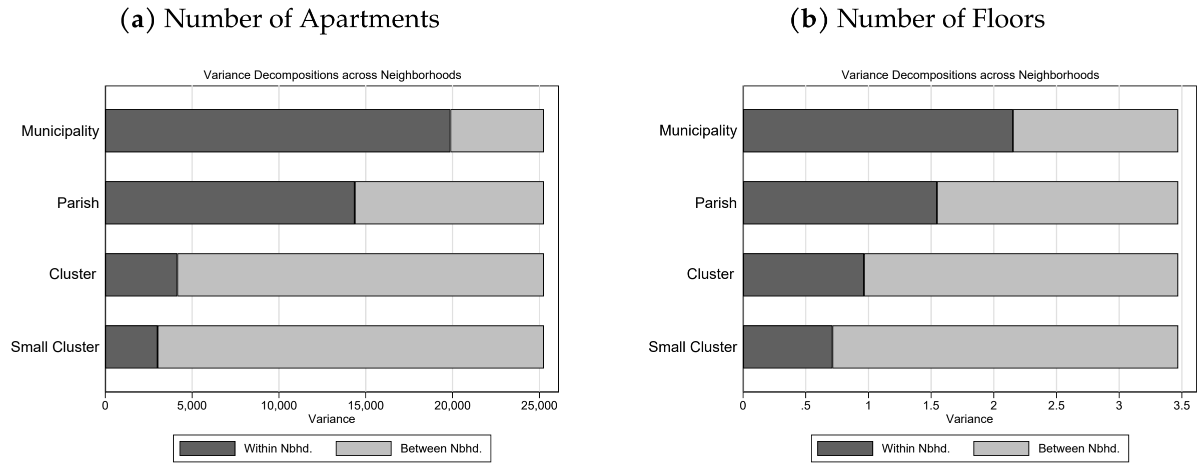
[4] The technical exposition is based on Jenkins (2021).

divided by the sum of the weights for the full estimation sample. $GE_k(a)$, inequality for subgroup k, is calculated as if the subgroup were a separate population, and $GE_B(a)$ is derived assuming every person within a given subgroup k received k's mean income, m_k.

E.1 Variance Decomposition of Housing Characteristics

Figure E.1 presents a simple variance decomposition of building characteristics across different neighborhood units in Denmark. The patterns are similar to the Theil's T decomposition approach.

Figure E.1: Variance Decomposition of Housing Characteristics across Neighborhoods

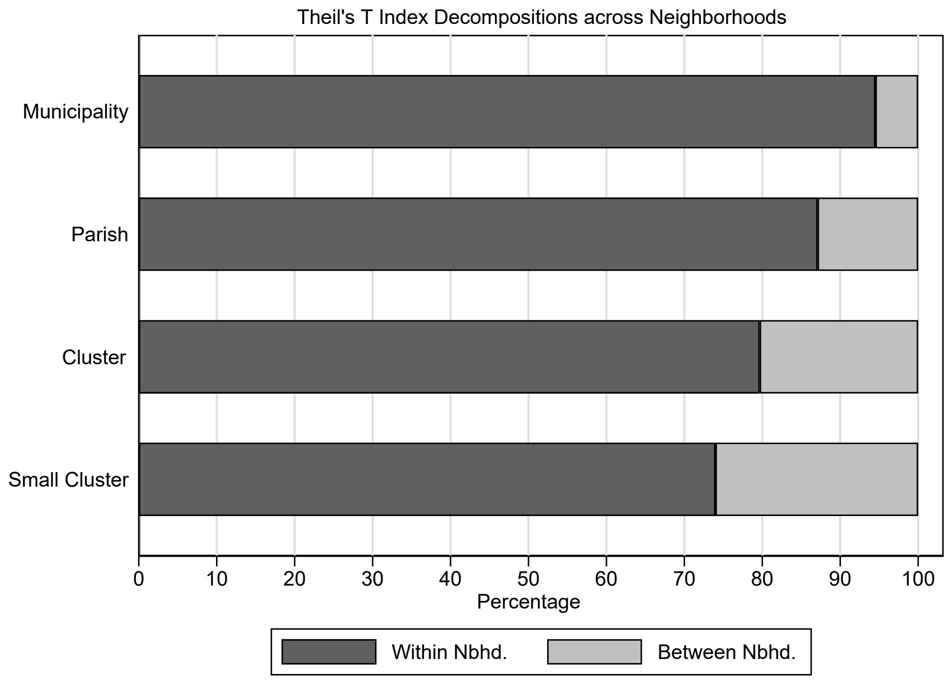


Notes: This figure presents the variance decomposition of building characteristics across different neighborhood units in Denmark. Panel (a) focuses on the number of apartments and Panel (b) shows the statistics for the number of floors.

E.2 Decomposition of Income Inequality

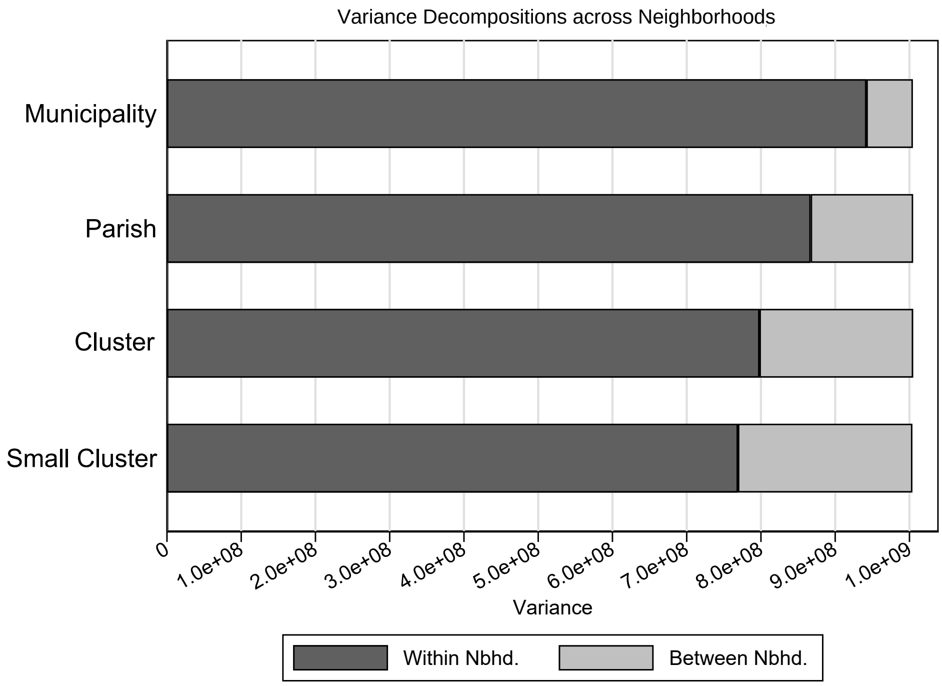
We also analyze the spatial decomposition of income inequality across neighborhoods in Denmark using the Theil's T Index. Figure E.2 presents the Theil's T decomposition of family income across different neighborhood units in Denmark, i.e., municipality, parish, cluster, and small cluster levels. Also, Figure E.3 presents the variance decomposition of family income across different neighborhood units in Denmark, which shows patterns simialr to Figure E.2.

Figure E.2: Theil's T Decomposition of Family Income across Neighborhoods



Notes: This figure presents the Theil's T decomposition of family income across different neighborhood units in Denmark. The disposable income is used as the measure of income. Family income is averaged over 2010–2015.

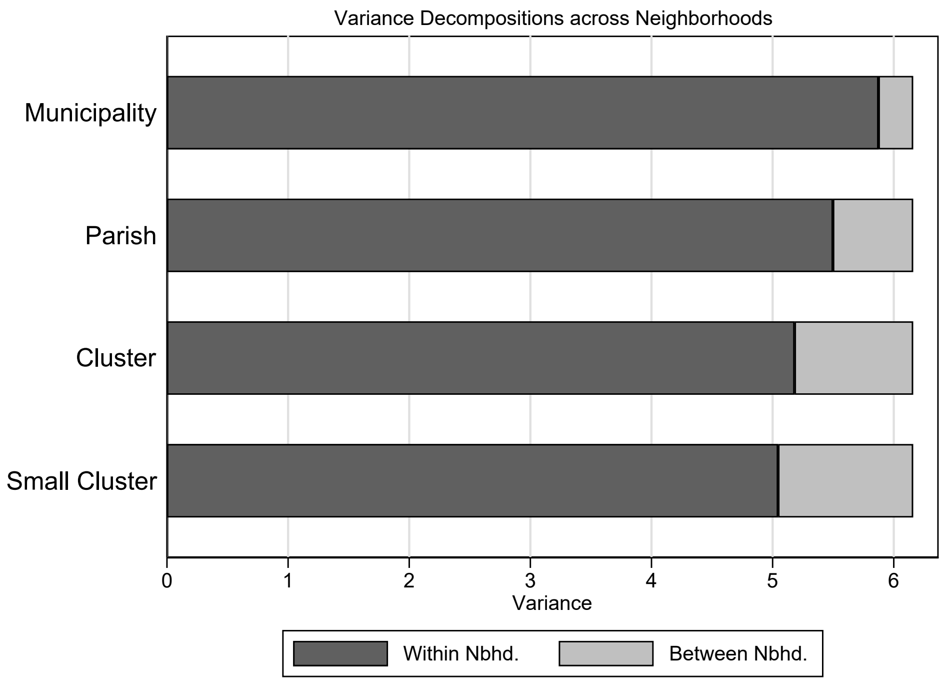
Figure E.3: Variance Decomposition of Family Income across Neighborhoods



Notes: This figure presents the variance decomposition of family disposable income across different neighborhood units in Denmark. The disposable income is used as the measure of income. Family income is averaged over 2010–2015.

Overall, our results suggest that families who reside in the same cluster are much more alike in terms of their observed characteristics, compared to the pool of families who live in the same parish or municipality. The results presented here focuses on income measures, but we observe a similar pattern when we look at other characteristics such as education level (see Figure E.4).

Figure E.4: Variance Decomposition of Education Levels across Neighborhoods

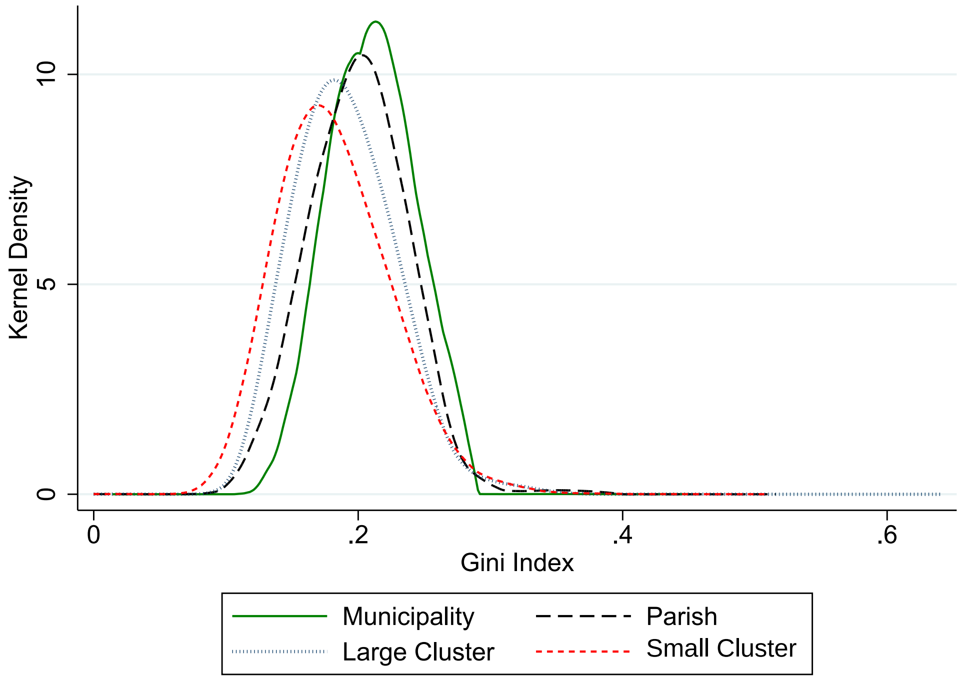


Notes: This figure presents the variance decomposition of education level of residents across different neighborhood units in Denmark. The completed years of schooling are used as the measure of education level.

E.3 Gini Index

We use the Gini Index measure to analyze the the income inequality at different neighborhood units in Denmark. Figure E.5 plots the distribution of neighborhood Gini index for various neighborhood units, i.e., municipality, parish, cluster, and small cluster, which shows that the income inequality is dramatically lower at cluster levels, suggesting more homogeneity among individuals living close to each other in a our neighborhood unit.

Figure E.5: Gini Index Kernel Density by Neighborhood Unit

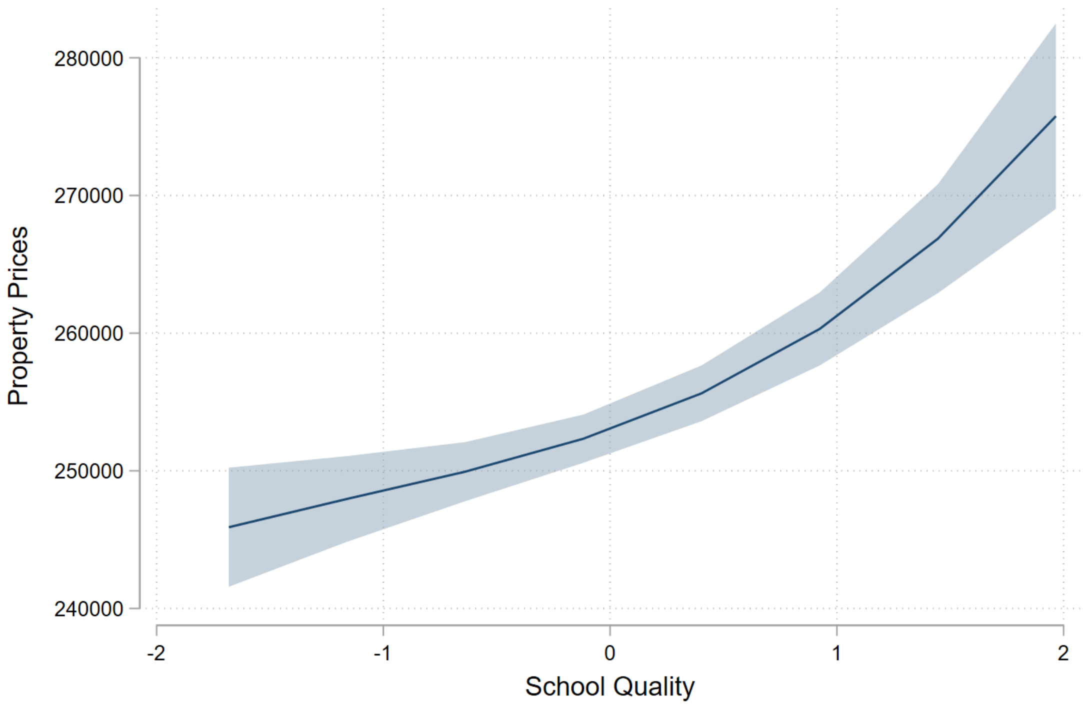


Note: Kernel density of neighborhood Gini coefficient of household income inequality in Denmark, 2015. The disposable income is used as the measure of family income. Family income is averaged over 2010-2015. The right axis (dash-dot line) indicates the ratio of segregation using parishes to that using clusters.

F Local Linear Hedonic Price Function

To explore the heterogeneity of the WTP over the distribution of school quality, this Appendix provides local linear estimates of the WTP, controlling for the same neighborhood and housing characteristics as well as fixed effects at the cluster-by-cohort level. Specifically, Figure F.1 depicts the nonlinear relationship between house prices and school quality—the hedonic price function. Its slope reflects the WTP for school quality.

Figure F.1: LOCAL LINEAR ESTIMATES OF THE WTP



Notes: The figure shows a local linear fit of the relationship between property prices and school quality, after controlling for neighborhood and housing characteristics, as well as cluster-by-cohort fixed effects. School quality is measured by taking the average test scores of students attending a given school. The sample contains property values for parents who have a child attending the ninth school grade between 2002 and 2006.

G An Overview of Diegert et al. (2022)

To address omitted variables bias, researchers have relied on sensitivity analyses which bound estimates when there is selection on unobservables. These methods, developed by Altonji et al. (2005) and refined by Oster (2019), require an exogeneity assumption implying that omitted variables are uncorrelated with the included controls.

The method proposed by Diegert et al. (2022) relaxes this strong assumption. It allows analysts to use one, two or three different sensitivity parameters to bound the parameter of interest in the presence of endogenous unobservables. The first parameter, $\bar{r}_X$, captures the relative magnitude of selection on unobservables and selection on observables, i.e., the proportion of the variance explained of WTP due to unobservables compared to observables. The second sensitivity parameter, $\bar{r}_Y$, measures the relative magnitude of the effect of unobservables on the outcomes. Finally, the third sensitivity parameter, $\bar{c}$, captures the level of endogeneity – the relationship between the observables and unobservables.

This approach doesn't require analysts to set all three parameters simultaneously. Theorem 2 of Diegert et al. (2022) characterizes the identified set for the parameter of interest in a regression with both observed and unobserved covariates using only $\bar{r}_X$ as a sensitivity parameter.[5] Their work characterizes the *breakdown point*, $\bar{r}_X^{bp}$, which is the largest amount of selection on unobservables under which in the population our coefficient of interest – the WTP for school quality – would still be nonnegative. We use this result to compute the breakdown point of $\bar{r}_X^{bp} = 61\%$ presented in the main text. We note that in their framework, the breakdown point cannot be greater than 100%.

Key to the computation of the breaking point is the choice of covariates. Our approach here is to use our specification presented in Section **??**, where we include a large set of small-cluster-by-school-catchment-area level attributes and housing characteristics. We first residualize the data using our small neighborhood level fixed effects. The breaking point is then to be interpreted in light of the number of relevant controls that are included in the regression of interest, comprising in our case of $\boldsymbol{X}$ and $\boldsymbol{H}$, the

[5] This is in contrast with the analysis of Oster (2019), where two tuning parameters need to be chosen.

neighborhood and housing characteristics.

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