The Impact of Open Enrollment on School Quality Premium in Housing Prices *

Rosie Li

November 5, 2025

Please click here for the latest version.

Abstract

Intra-district open enrollment reduces the link between locations and local school quality. This paper estimates the impact of open enrollment on the housing market and on residential sorting in large school districts across the U.S. I employ a spatial boundary discontinuity design (RD) to estimate the causal effects of neighborhood school quality on housing prices by district-level open enrollment policy adoption status and by time period. Then I employ a difference-in-differences framework to quantify the effect of open enrollment on the capitalization of neighborhood school quality in housing prices after 2014. I find that districts implementing open enrollment experienced a 1.7 percentage-point decline, relative to districts without open enrollment, in neighborhood school quality capitalization effects estimated at around 5% for one standard deviation of school quality in the initial period. Further, using linked data on demographic characteristics of home buyers, I find that open enrollment reduced residential sorting on income along school attendance boundary lines.

*Yale University Economics Ph.D. candidate (job market paper). I am grateful to Joseph Altonji, Jason Abaluck, and John Eric Humphries for their generous guidance and support. I also thank Barbara Biasi, Paul Goldsmith-Pinkham, Costas Meghir, Marius Ring, and Seth Zimmerman for their comments and suggestions, as well as participants at the Yale Labor/Public Economics Prospectus Workshop for their feedback. Contact email: rosie.li@yale.edu.

1 Introduction

Intra-district open enrollment, which allows students to apply for transfers from their assigned neighborhood schools to other public schools within the district, has emerged as an important school choice policy in the U.S (Abdulkadiroğlu & Sönmez, 2003). Compared with traditional neighborhood school systems, it expands access to high-quality schools and encourages competition among traditional public schools (Hoxby, 2000).

In this paper, I study the impact of open enrollment on the housing market and residential patterns. If open enrollment does reduce the link between residences and schools, the relationship between neighborhood school quality and housing prices should become weaker. Sorting on socioeconomic characteristics along school attendance boundary lines should also be reduced. Therefore, I ask the following research questions: Does open enrollment decrease the capitalization of neighborhood school quality in housing prices and to what extent? How does open enrollment affect residential choices of home buyers?

Much of the research on intra-district open enrollment has focused on one single school district in large metropolitan areas (Abdulkadiroğlu et al., 2017; Campos & Kearns, 2024). Yet in recent years, open enrollment increasingly takes place in large school districts beyond major cities. Despite this trend, we know little about the impact of open enrollment at scale.

In this paper, I quantify the effect of open enrollment on neighborhood school quality premium in housing prices in large school districts across the U.S. There are two challenges to studying open enrollment across geographical areas. First, open enrollment policies are implemented on the district level, making it difficult to adopt a research design using state-level policy variation. I construct a new dataset on open enrollment policies for 235 large school districts by collecting current policy information and combining it with historical policy data in 2012. Second, studying multiple districts requires the measures and methods to be uniform in the samples of interest. I link data on school attendance boundaries, school characteristics, and property transactions. The SEDA measure of school performance (Fahle et al., 2024) provides one dimension of school quality that is comparable across geographical areas. I then employ a difference-in-differences framework to estimate the difference in differences in discontinuities, to study how capitalization of neighborhood school quality changes in districts that implemented open enrollment relative to those that did not.

The study also provides some evidence on the effectiveness of open enrollment in promoting school choice. On the one hand, open enrollment expands choice sets within reasonable commuting distances more drastically, compared with inter-district open enrollment and charter schools. On the other hand, its impact could be mitigated by factors such as capacity constraints at high-demand schools, information friction, and lack of district-provided transportation. Therefore, the effect of open enrollment on school choice remains an empirical question. The results of this paper suggest that open enrollment widens access to schools to some degree, but does not fully eliminate the link between locations and school quality.

I first document that the share of 235 large districts offering open enrollment increased from 11% to 76% over this period. Since these districts educate 28 percent of U.S. elementary school students, this growth implies that elementary student access to open enrollment rose from at least 3% in 2012 to at least 22% by 2025 [1]. Using the open enrollment policy adoption data in 2012 and 2025, I construct three policy types of districts: early open enrollment adopters (which had open enrollment by 2012), open enrollment switchers (which had no open enrollment in 2012 but open enrollment in 2025), districts with no open enrollment (which had no open enrollment in 2012 or 2025).

I employ a spatial boundary discontinuity model to obtain causal estimates of neighborhood school quality capitalization in housing prices from 2010 to 2024. I construct buffer zones around school attendance boundaries, so that the properties I study are in geographical proximity to school attendance zone borders. This allows me to compare otherwise similar houses assigned to different schools. I compute capitalization estimates by year and by district policy type. The estimates allow me to characterize the trends in the local school quality premium in housing prices over time. I find that capitalization

[1] I calculated these statistics using 2012 enrollment data.

effects of open enrollment switchers and districts with no open enrollment are similar to each other in initial years, but starting around 2015 the effects of open enrollment switchers declined relative to districts with no open enrollment.

To quantify the effect of open enrollment on housing prices, I employ spatial boundary discontinuity and difference-in-differences methods to estimate a difference in differences in discontinuities. The combined model allows me to estimate the magnitude of decline in the capitalization of neighborhood school quality in housing prices for open enrollment switchers and early open enrollment adopters separately, relative to districts with no open enrollment.

I find that in districts that switched to open enrollment, the relationship between housing prices and neighborhood school quality weakened relative to districts without open enrollment after 2014. Specifically, a one-standard deviation increase in local school quality is valued 1.7 percentage points less, decreasing from 5% in the initial period. For districts that adopted open enrollment early, I observe a similar decrease of 2.5 percentage points, which occurred in the pre-2015 period rather than the post-2015 period.

To further test whether the decline in local school quality premium is attributed to changes in access to schools, I link L2 voter data to CoreLogic property data to obtain information on whether buyers have children. I classify buffer zones of school attendance boundaries into two groups, based on whether the fraction of buyers with children is above median in my analysis sample. I show that in districts which switched to open enrollment, the relative decline in local school quality premium is larger in areas with above median proportions of buyers with children. I find similar patterns in districts which adopted open enrollment early. This suggests that the reduction in the capitalization of neighborhood school quality in housing prices is greater in areas where neighborhood school quality is more likely viewed as an amenity by buyers. It provides evidence that supports changes in access to schools as the causal factor rather than changes in other amenities unrelated to education.

To study the effect of open enrollment on residential choice patterns, I use L2 data to obtain demographic and socioeconomic information of home buyers. I am able to obtain estimated income information for 60% of buyers in CoreLogic data. I apply a spatial boundary discontinuity method to estimate the causal effect of neighborhood school quality on buyer income. This provides a measure of annual income disparity among buyers per one standard deviation of neighborhood school quality. Using the same research design that incorporates regression discontinuity (RD) and difference-in-differences (DiD), I quantify the effect of open enrollment on residential sorting along school attendance boundary lines. I find that districts implementing open enrollment experienced an additional decrease of approximately $1,768 in the annual income disparity among buyers per one standard deviation of neighborhood school quality.

I address concerns related to the empirical identification. In the main analyses, I focus on districts with a low share of enrollment in charter or magnet schools by 2019, which yields 56 large districts covering a wide geographical span. To address the limitation that the exact years of open enrollment policy enactment are not available, I conduct a case study of three school districts where the years of open enrollment implementation are known. I document a decrease of capitalization effects of 1.6%, similar to that in the main analyses. I also create a randomly generated policy indicator among open enrollment switchers, and find the difference-in-differences coefficient to be around zero. This serves as a useful check against bias from spatially correlated unobservables.

This paper contributes to three strands of the literature. The first strand of literature is on the capitalization of neighborhood school quality in housing prices, or the valuation of local school quality. The key parameter of interest is typically estimated with panel data methods (Figlio & Lucas, 2004) or boundary discontinuity methods (Black, 1999; Black & Machin, 2011). The paper employs the boundary discontinuity method. It contributes to this literature by presenting the capitalization effects from 2010 to 2024 across a large number of districts, providing estimates for recent years. It also demonstrates that these effects are more pronounced in areas with higher proportions of buyers who are parents.

The second strand of literature is on the effect of school choice on the capitalization effect. Early work examines the effect of *inter*-district open enrollment on housing prices and finds that districts with lower school quality experienced growth in housing prices after *inter*-district open enrollment was introduced (Chung, 2015; Reback, 2005). On charter schools, recent research finds that the introduction of charter schools decreased the valuation of local school quality by 3 percentage points (Zheng, 2022). More recently, Wigger (2025) documents that Denver, Colorado, which implemented an intra-district open enrollment reform, experienced a decline in the capitalization of neighborhood school quality in housing prices over time. I contribute to this strand of literature by studying open enrollment in multiple school districts covering a large geographical span across the U.S.

The third strand of literature is on education policy and residential sorting. Tiebout sorting (Tiebout, 1956) can arise along school administrative boundaries, as school is one of the most important public goods. Past research has shown that when education quality improves in neighborhoods with lower school quality in the form of increased expenditure (Chakrabarti & Roy, 2015), these neighborhoods experience an increase in the fraction of higher-income residents. I contribute to this literature by document changes in sorting within districts, following open enrollment. In addition, I introduce more granular data at the individual level, moving beyond aggregate statistics.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the trends in the capitalization effects of neighborhood school quality in housing prices by district policy types, estimated using spatial boundary discontinuity methods. Section 4 quantifies the decline in the capitalization effects in districts which implemented open enrollment relative to districts that did not. Section 5 discusses results on residential sorting. Section 6 conducts a case study of three school districts for which the years of open enrollment implementation are known. Section 7 presents robustness checks. Section 8 concludes.

2 Data

I build a dataset linking school attendance boundaries, school characteristics, local charter and magnet school presence, property transactions, and demographic information of buyers at the national level.

2.1 Property transactions

Housing price data are provided by CoreLogic. I merge tax files and owner transfer files to obtain information on transacted sale prices, sale dates, housing locations and housing characteristics. I focus on single family residences that are owner occupied, and that are arm-length transactions. I exclude foreclosed properties and keep residences between 100 to 10000 square feet and between $\$10,000$ and $\$14.5$ million in transacted prices. I construct inflation-adjusted housing prices, using the Consumer Price Index for All Urban Consumers: All items (CPIAUCSL) from the Federal Reserve Bank of St. Louis. Year 2010 is used as the benchmark to construct real housing prices in 2010 dollars.

2.2 School Attendance Boundaries

Data on school attendance boundaries come from the School Attendance Boundary Survey 2015-2016 by National Center for Education Statistics. Given that only one year of attendance boundary data is available, this could lead to mis-measurements of assigned school quality when school attendance boundaries change. However, school attendance boundaries change infrequently. Less than 3% of elementary schools changed boundaries between 2010 and 2014 in FL, TN, NY and MA (Zheng, 2022). I focus on elementary school attendance zones [2], excluding school attendance boundaries for kindergartens. School attendance zones sometimes overlap with each other. In this case, I drop schools with large catchment zones that contain the attendance zones of other schools. [3]

[2] I use the definition of elementary schools provided in the dataset.
[3] I use the USA Contiguous Albers Equal Area Conic geographical coordinate system.

2.3 The National Longitudinal School Database and SEDA

I use The National Longitudinal School Database (NLSD) (Carroll et al., 2023) for school-level information on school locations and school enrollment. I use the school performance data from Stanford Education Data Archive (SEDA) (Reardon et al., 2023) as a proxy for school quality, with the caveat that test score performance reflects not only the capabilities of schools to provide education, but also the composition of student family backgrounds across schools. Importantly, this measure is constructed using the National Assessment of Educational Progress (NAEP) as a benchmark. NAEP is administered to a random sample of students in every state in grades 4 and 8 in Math and Reading every two years. SEDA estimates a hierarchical linear model, which rescales local test scores to achievement measures that are comparable across states. This ensures the comparability of the estimates of capitalization effects across the U.S.

In addition, NLSD contains information on charter and magnet schools in each year. This enables the study of charter and magnet school presence in school districts. Charter schools often have their own school IDs. I use the geographical coordinates of charter schools and school attendance boundary files to infer the public school districts where the charter schools are located in. I calculate the share of students enrolled in charter and magnet schools each year in the school districts.

2.4 School District Student Assignment Policies

I focus on elementary schools, because policy information in 2012 is available only at this level. School district student assignment information in 2012 is obtained from IPUMS. Assignment policy information was collected for the largest 350 school districts in the United States (where size is determined by the number of public school students enrolled in the district as determined by the 2009-2010 Common Core of Data). I use this dataset to obtain information about district policies on open enrollment in 2012. The dataset contains one variable measuring whether students are allowed to attend any school within a district (or any school within a sub-region within a district).

I hand collect current information on *intra*-district open enrollment policies for these

350 districts. I define districts to have open enrollment if they allow students to transfer to other traditional public schools simply based on parental preference. Districts that maintain a small set of specialized schools or programs for choice but do not allow for general transfers within the traditional public systems are not classified as open enrollment districts. Almost all school districts allow for transfers under special circumstances like having experienced hardships or victim to bullying. However, not every districts allows for *intra*-district transfers in general. It is worth noting that within the districts that have open enrollment, the implementation is very different. Some key differences are whether the application process is centralized, whether available seats are determined through the lottery process, and the duration of the open enrollment period. In this project, I abstract away from modeling these details, although it would be worthwhile to investigate these effects of the implementation mechanisms in future work. I am able to collect the policy information in 2025 for 235 districts.

2.5 American Community Survey

I use the census-block-group-level 5-Year data from 2009-2013, 2013-2017, 2017-2021 and 2019-2023 (the latest year available) from the American Community Survey to obtain information on neighborhood attributes. [4] The datasets include five-year averages of neighborhood population counts by race, education and family structure. I extract information on percentages of residents who are White, Black, and Asian, Bachelor's degree completion rate, percentage of married families with children, and median income.

2.6 L2 Voter Data

The L2 voter data contains information on the imputed demographic information of registered voters in the US. I match the L2 data to CoreLogic data to obtain demographic information of buyers. Buyers represent the inflows to the neighborhoods, and provide

[4] The 2009-2013, 2013-2017, 2017-2021, and 2019-2023 values are assigned to transactions in 2010-2012, 2013-2016, 2017-2020 and 2021-2023, respectively.

forecasts for the trends of neighborhood composition.

I aggregate the demographic information on the household level, defined by the same last names and addresses. Specifically, I compute average income and highest education at the household level. If any individual in the household belongs to one race, I assign the racial category to that household. That is, a household gets an indicator for every race represented among its members. [5] I merge the L2 data to CoreLogic data using information on last names and addresses. I use the 2025, 2022, and 2020 data files for matching. The 2025 files contain granular numerical predictions of income, while the 2022 and 2020 files contain only categories of income. For categorical measurements of income, I take the median value of each category to obtain the imputed value. For example, the income category \$150,000-174,999 is imputed as \$162,499.5.

The match rate is 62% for imputed income, 58% for whether buyers have children, 57% for race, and 49% for education. In my sample, 64% of the buyer households have household members who are White, 8.3% Black and 19.6% Hispanic. 63% of households have members of bachelor's degree or above. The median income is $\$125,000$.

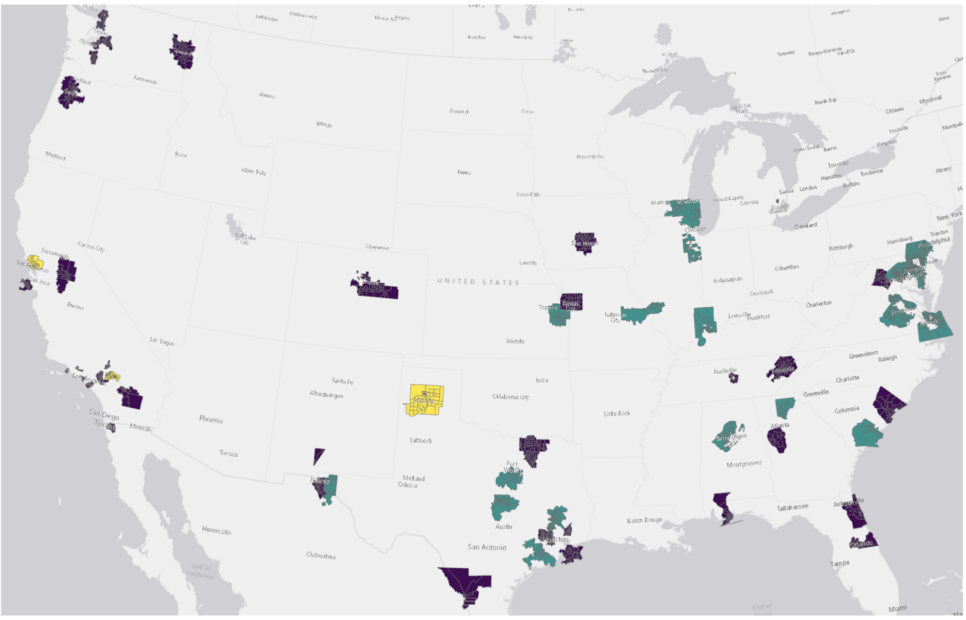
2.7 Classification of Districts by School Choice Policy Changes

In recent decades, concurrent with the growth of open enrollment, charter and magnet schools have expanded in many school districts. In order to limit the confounding effect of charter or magnet school choice, I identify 56 districts that had less than 5% of enrollment share in charter and magnet schools by 2019 to form the analysis sample.

After this operation, I define three groups based on their open enrollment policy types. The first group, which is labeled Open Enrollment Switchers, consists of districts which did not have open enrollment in 2012, but have open enrollment by 2025. The second group, which is labeled No Open Enrollment, includes districts with no open enrollment in 2012 or 2025. The third group, which is labeled Early Open Enrollment, is composed of districts which had open enrollment early on by 2012 and continues to have open

[5] The majority of the households in the sample are single-race households.

Figure 1: District-level School Attendance Boundary Maps



Notes: This figure plots the geographical locations of districts used in the analyses. The colors denote the policy types of the districts: dark green indicates districts with no open enrollment; dark purple indicates open enrollment switchers; yellow indicates early open enrollment adopters. The scale of the districts has been enlarged for a more clear display.

enrollment in 2025.

Figure 1 below shows a map of the school districts studied, where dark green color marks districts with no open enrollment, dark purple color marks districts that switched to open enrollment from 2012 to 2025, yellow color marks districts that adopted open enrollment by 2012. The attendance boundaries have been enlarged for visualization. The data variation comes from geographical regions across the U.S.

3 Trends in the Capitalization Effects of Local School Quality in Housing Prices

In order to characterize the impact of open enrollment, I estimate how the valuation of local school quality in housing prices change year by year, as school districts adopted open enrollment policies between 2012 and 2025. Here I do not study the districts which adopted open enrollment before 2012, due to their relatively small sample sizes.

3.1 Hedonic Regressions

I begin by running hedonic regressions of housing prices on school quality controlling for housing and neighborhood characteristics. I use the following specification:

$$y_{idst} = \alpha X_{it} + \sum_{t=2010}^{2024} \beta_t Qual_s \mathbf{1}_{\{Year==t\}} + \theta_{dt} + \varepsilon_{idst} \tag{1}$$

In the specification, i indexes individual properties, d indexes school districts, s indexes schools associated with property i, and t indexes sale year. y_{idst} denotes inflation-adjusted log housing prices. X_{it} are controls which consist of house and neighborhood characteristics. The house-level covariates include log square feet, year built, lot size, the number of bedrooms, the number of bathrooms, whether the property has parking, whether it has a basement, the number of stories, and the number of rooms. Missing values are coded as a separate category for the number of bathrooms, bedrooms, stories, and total rooms.

The neighborhood characteristics are at the census block group level, using data from ACS. For property transactions between 2010 and 2013, I assign the 2009-2013 ACS rolling averages of census-block-group-level demographic and socioeconomic characteristics. Similarly for property transactions between 2013 and 2017 as well as between 2017-2021, I assign the ACS values from the corresponding 5-year period. For property transactions after 2021, I assign the 2019-2023 ACS values. The covariates include racial composition, average rate of bachelor's degree completion, percentage of married families with children, and median income. As Bayer et al. (2007) first points out, there are clear discontinuities of resident demographic characteristics at the school attendance boundaries. Failing to take into account such sorting would significantly overestimate the capitalization effect. I also control for an indicator variable of whether a house is located in a census block group intersected by different attendance boundaries.

The local school quality is measured using the mean achievement level measure constructed by Stanford Education Data Archive, as discussed in the data section. The comparability of this measure across different states allows me to compare estimates across different policy types of districts. However, it is important to note that this quality measure does not equate to the capabilities of schools, but rather the academic performance of schools due to various factors including the socioeconomic composition of students.

I interact school quality measures (denoted by $Qual_s$) with sale year dummies (denoted by $\mathbf{1}_{\{Year==t\}}$) to capture the changes in the relationships between housing prices and school quality by year. Specifications that interact the school quality with year indicators have been used in Wigger (2025) and Zheng (2022). θ_{dt} are district-year fixed effects. Given the long span of time and large number of districts studied, I adopt this more flexible fixed-effect specification and allow the districts effects to be non-linear in time.

Figure 2 shows that open enrollment switcher districts saw similar relationships between housing prices and school quality to those in districts with no open enrollment in the initial years. However, the correlation declined relatively more in open enrollment switcher districts after 2012, and showed a divergent trend compared with districts with no open enrollment.

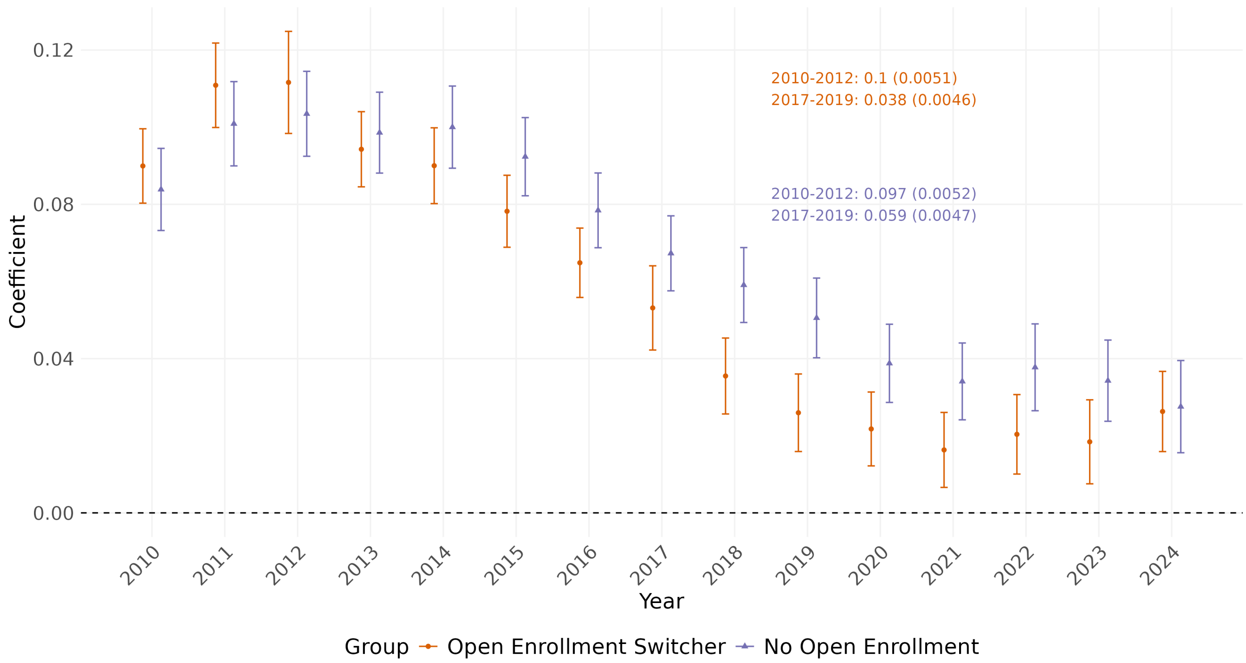
After 2020, the correlation between housing prices and school quality also declined significantly in districts with no open enrollment.

3.2 Spatial Regression Discontinuity

Hedonic regressions cannot provide causal identification, because neighborhood characteristics are confounders which bias the estimated regression coefficient on school quality upward. To address this challenge, I follow the standard practices of exploiting variation with attendance boundary buffer zones in the literature, pioneered by Black (1999).

I examine houses located close to the school attendance boundaries. The geographical proximity makes the assumption that houses on different sides of attendance boundaries have access to the same neighborhood amenities more tenable. I exclude boundaries that also overlap with school district boundaries, as different districts may have different property tax rates. I construct buffer zones of 0.3 miles around the school attendance boundaries. When a house is close to multiple boundaries of difference school attendance zones, I assign it to the boundary of the closest distance. Then, I exploit the variation in

Figure 2: Hedonic Regressions



Notes: This figure shows the empirical correlation between neighborhood school quality and housing prices. The x-axis describes the sale year. The y-axis plots the regression coefficient on the interaction terms between school quality and the sale year dummies on x-axis in a hedonic regression of housing prices on school quality and controls, including district-year fixed effects. Error bars represent 95 percent confidence intervals.

neighborhood school quality within buffer zones in the same year to estimate the causal effect of neighborhood school quality on housing prices.

Formally, the specification is:

$$y_{ibst} = \alpha X_{it} + \sum_{t=2010}^{2024} \beta_t Qual_s \mathbf{1}_{\{Year==t\}} + \theta_{bt} + \varepsilon_{ibst} \quad (2)$$

In the specification, i indexes individual properties, d indexes school districts, s indexes schools associated with property i, and t indexes sale year. The definitions of variables are the same as before, and I keep the same set of control variables. I control for buffer-zone-year fixed effects (denoted by θ_{bt}), key to the implementation of the spatial RD design. With the inclusion of buffer-zone-year fixed effects, the identifying variation comes from the differences in local school quality at opposite sides of school attendance borders in a given year. Therefore, the interactions between local school quality measures (denoted by $Qual_s$) with sale year dummies (denoted by $\mathbf{1}_{\{Year==t\}}$) capture the changes in the local school quality premium in housing prices over time.

Table 1 reports the descriptive statistics on different sides of boundaries for districts that switch to open enrollment and districts that have no open enrollment. As expected, there are large differences in school quality at different sides of the school attendance boundaries. The housing characteristics have small differences across borders for both open enrollment switcher districts and no open enrollment districts. These differences are statistically significant, given the large sample size, but are small in magnitudes. There are discontinuities in neighborhood demographics, especially in the median income. Appendix table A1 reports the same descriptive statistics for districts that are early open enrollment adopters, compared with districts that have no open enrollment. The patterns are very similar. Appendix table A2 reports results of regressions of school quality on a composite measure of housing quality. The housing quality is constructed using a principal component analysis. Housing quality tends to be higher in attendance boundaries with higher test scores: a one-standard deviation increase in housing quality is associated with a 0.018 standard deviation increase in local school quality. This may be because some school attendance boundaries have inherited the vestiges of the historical neighborhood configuration, such as the Home Owners' Loan Corporation (HOLC) redlining maps (Monarrez & Chien, 2021). However, there is no indication that this relationship differs by types of school districts. In addition, I measure the changes in the capitalization effects, which are not impacted by time-invariant characteristics.

Figure 3 plots the capitalization effects over time, estimated by the spatial regression discontinuity models. While the by-year estimates are somewhat noisy, the results show a gradual decline of the capitalization effects in open enrollment switcher districts after 2012.

On the top right of the figure, I report the estimated regression coefficients on school quality for regressions pooling 2010-2012 and pooling 2017-2019, in order to obtain more precise estimates. The capitalization effects are estimated to be 0.06 in 2010-2012 and decreased to 0.025 in 2017-2019 in the open enrollment switcher districts. Meanwhile in districts with no open enrollment throughout this period, the capitalization effects changed from 0.048 to 0.036, a much more modest decline.

Appendix table A4 reports the coefficients plotted on the figure for each year.

3.3 Alternative Regression Discontinuity Specification

To provide more evidence on discontinuity at the border, I estimate an alternative RD specification adapted from that of Ring (2025). In this version, I examine changes before and after 2015 rather than by year and define finer geographical groups. Specifically, I divide observations in the 0.3-mile (approximately 480 meters) buffer zones into eight bins based on their distances to the borders. Hence, the bins represent houses within 0-120 meters, 120-240 meters, 240-360 meters, or 360-480 meters to the border on either side of the attendance boundaries. I use a negative sign in front to denote bins on the lower test score side.

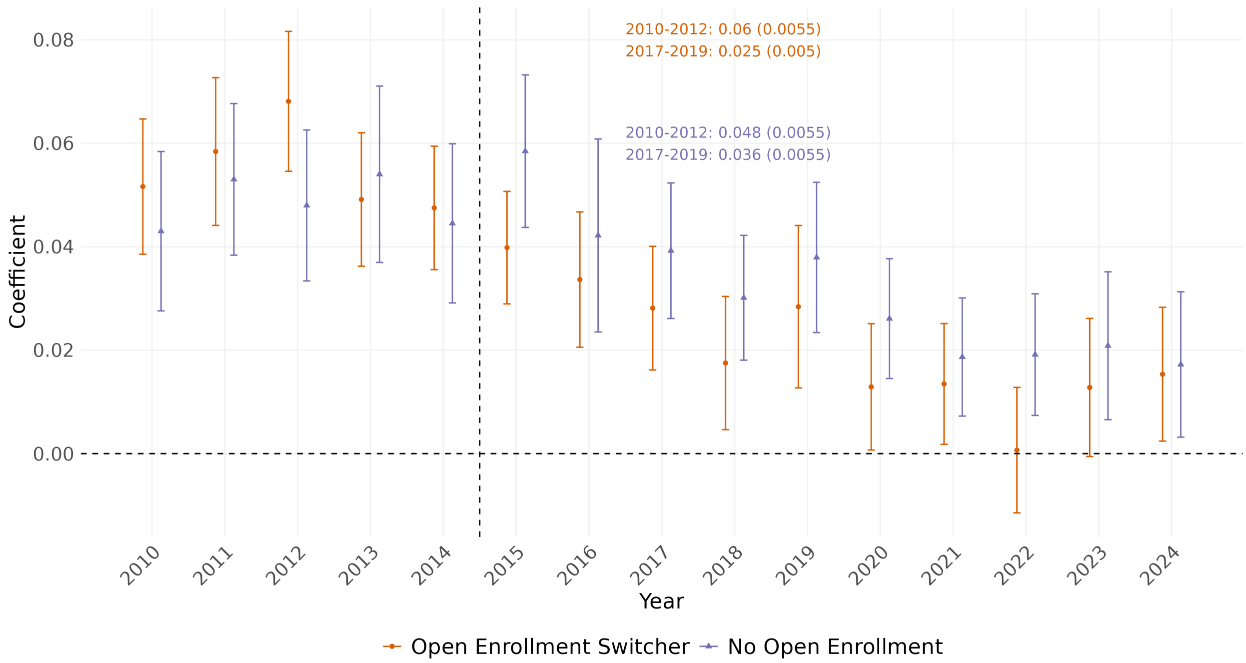
Let D_i denote distance of house i to the border of the buffer zone it belongs to. Let B_j denote the distance bins where $B_j \in \{-480 - 360m\}, \{-360 - 240m\}, \{-240 - 120m\}, \{0 - 120m\}, \{120 - 240m\}, \{240 - 360m\}, \{360 - 480m\}$. The $\{-120 - 0m\}$ group

Table 1: Descriptive Statistics Comparing Open Enrollment Switchers and No Open Enrollment Districts

	OE Switcher		No OE	
Variable	High Score Side	Low Score Side	High Score Side	Low Score Side
Observation	219,230	218,093	196,671	184,547
Sale price	399,560	379,366	372,408	359,110
(nominal dollars)	(355,318)	(296,939)	(283,178)	(270,217)
House characteristics				
Log square foot	7.63	7.58	7.66	7.63
	(0.44)	(0.43)	(0.41)	(0.42)
Lot size (acres)	0.28	0.27	0.35	0.35
	(0.75)	(0.74)	(0.70)	(0.71)
Number of baths	3.65	3.55	3.70	3.64
	(1.22)	(1.21)	(1.19)	(1.21)
Year built	1,984.32	1,982.97	1,982.02	1,981.34
	(24.10)	(24.74)	(24.90)	(24.84)
Has parking	0.82	0.81	0.67	0.65
	(0.38)	(0.39)	(0.47)	(0.48)
Has basement	0.25	0.25	0.34	0.34
	(0.43)	(0.43)	(0.47)	(0.47)
Number of stories	1.79	1.72	2.12	2.07
	(0.96)	(0.94)	(0.95)	(0.96)
Total rooms	5.04	4.88	5.27	5.06
	(1.67)	(1.64)	(1.60)	(1.57)
School quality				
SEDA	0.65	0.10	0.88	0.38
(standardized)	(0.92)	(0.90)	(0.82)	(0.80)
Place attributes				
Median HH income	102,051.41	97,667.33	108,502.04	103,943.97
	(46,722.34)	(45,755.74)	(47,126.27)	(47,112.92)
Percent White	0.69	0.68	0.66	0.65
	(0.22)	(0.22)	(0.22)	(0.23)
Percent with	0.43	0.40	0.44	0.43
bachelor's or higher	(0.21)	(0.20)	(0.21)	(0.21)

Notes: Summary statistics in 2010-2024 for districts which switched to open enrollment (first and second column) and for districts with no open enrollment during this period (third and fourth column). The first and third column reports descriptives for the higher test score side, while the second and fourth column for the lower test score side. The means are present, with standard deviation in the parentheses.

Figure 3: RD Estimated Trends in the Capitalization of Neighborhood School Quality



Notes: This figure shows the causal effect of neighborhood school quality on housing prices. The x-axis describes the sale year. The y-axis plots the regression coefficient on the interaction terms between school quality and the sale year dummies on x-axis in a boundary discontinuity regression of housing prices on school quality and controls, including boundary-year fixed effects. Error bars represent 95 percent confidence intervals.

is omitted and serves as the reference group. ΔQ_b is the difference in quality between the higher and lower test score side of a given attendance zone border. $\mathbb{1}\text{Post } 2014_t$ is an indicator variable which takes on 1 if the sale year is 2015 or later.

The specification is:

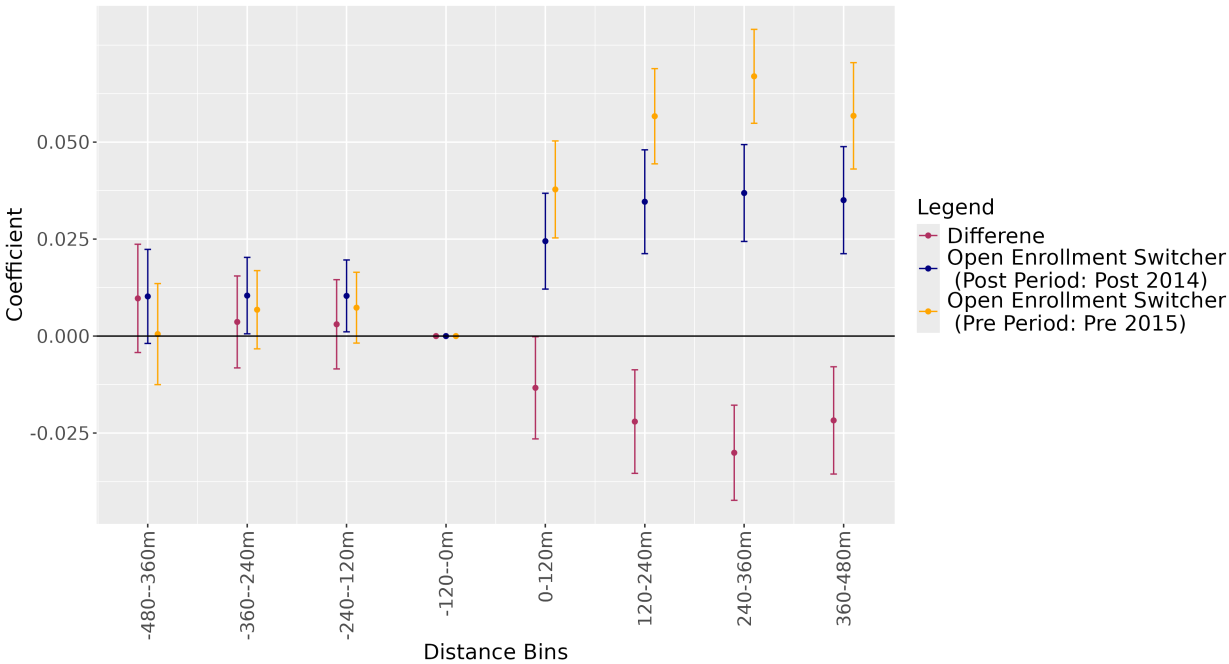
$$\begin{aligned} y_{ibst} = \alpha X_{it} + \gamma_1 \Delta Q_b + \sum_{j=1}^{7} \beta_j \Delta Q_b \times \mathbf{1}_{\{D_i \in B_j\}} + \\ \gamma_2 \Delta Q_b \times \mathbb{1}\text{Post } 2014_t + \sum_{j=1}^{7} \delta_j \Delta Q_b \times \mathbf{1}_{\{D_i \in B_j\}} \times \mathbb{1}\text{Post } 2014_t + \\ \theta_{bt} + \varepsilon_{ibst} \end{aligned} \tag{3}$$

The coefficients β_j capture the differences in housing prices at different distance bins relative to the $\{-120 - 0m\}$ group in the pre-2015 period when the school quality difference is one standard deviation across borders. The coefficients δ_j capture the difference in differences in housing prices at different distance bins relative to the $\{-120 - 0m\}$ group in the post period relative to the pre period.

Figure 4 shows results for open enrollment switchers and plots β_j in yellow (pre-2015 estimates). The coefficients in distance bins on the lower test score side are close to 0, while the coefficients on the higher test score see a jump at the 0-120m bin. This suggests that there is indeed a discontinuity in housing prices at the border. The blue points correspond to the coefficients $\beta_j + \delta_j$ for the post-2014 period. The discontinuity in housing prices is significant smaller in the post period, suggesting that open enrollment reduced the school quality premium. The red points indicate δ_j, the magnitude of the decrease in discontinuities in the post period relative to the pre period. Figure 5 shows results for districts with no open enrollment with the same color scheme. While there is a jump of similar magnitude in housing prices at the 0-120m distance bin in the pre-period, the discontinuity changed very little in the post period, with a small decrease in the 360-480m bin.

These figures suggest that open enrollment switchers experienced a substantial decline in school quality premium in housing prices after 2014, while districts with no open

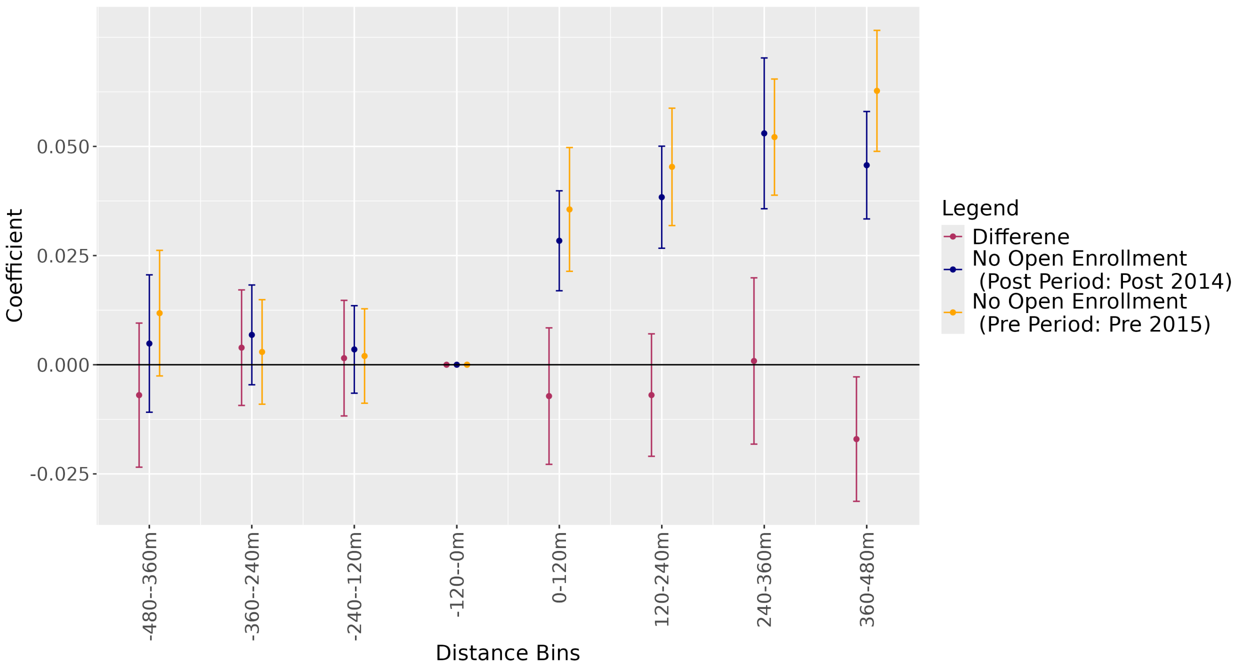
Figure 4: RD Coefficients on Quality X Distance Bins for Open Enrollment Switcher Districts by Time Period



Notes: This figure shows the differences in housing prices at different distance bins in the pre and post period when the school quality difference is one standard deviation across borders, for districts that are open enrollment switchers. The x-axis shows distance bins based on distances to the borders, with a negative sign indicating the lower test score side. The coefficients for the -120-0m bin are normalized to 0. Error bars represent 95 percent confidence intervals.

enrollment did not.

Figure 5: RD Coefficients on Quality X Distance Bins for Districts with no Open Enrollment by Time Period



Notes: This figure shows the differences in housing prices at different distance bins in the pre and post period when the school quality difference is one standard deviation across borders, for districts with no open enrollment. The x-axis shows distance bins based on distances to the borders, with a negative sign indicating the lower test score side. The coefficients for the -120-0m bin are normalized to 0. Error bars represent 95 percent confidence intervals.

4 Quantification of the Decline

After establishing that there has been a declining trend in the capitalization effects in districts which switched to open enrollment relative to districts with no open enrollment, I quantify the magnitude of the relative decline. I combine regression discontinuities with a difference-in-difference specification to estimate the effect of open enrollment on capitalization effects. I estimate the specification separately for open enrollment switchers and early open enrollment adopters, with districts that have no open enrollment as the control group in both cases. I classify 2010-2014 as the pre-period and 2015-2019 as the post-period. I also present results where I classify 2015-2024 as the post-period.

Mathematically, I adopt the following specification:

$$\begin{aligned} y_{isbt} = \alpha X_{it} + \theta_{bt} + \delta_1 \text{Qual}_s + \delta_2 \mathbb{1}\text{Post } 2014_t \times \text{Qual}_s + \\ \delta_3 \mathbb{1}\text{OE District}_d \times \text{Qual}_s + \\ \delta_4 \mathbb{1}\text{OE District}_d \times \mathbb{1}\text{Post } 2014_t \times \text{Qual}_s + \varepsilon_{isbt} \end{aligned} \tag{4}$$

The specification includes the interaction between school quality and an indicator variable of being in a district with open enrollment, the interaction between school quality and an indicator variable for years post 2014, and a triple interaction term of school quality, treatment indicator, and time indicator.

The first column of table 2 shows results using the analysis period 2010 to 2019, while the second column analyzes a longer period from 2010 to 2024, to understand trends in the last few years as well. The results show that the capitalization of school quality in housing prices declined 1.7% in districts that switched to open enrollment relative to districts with no open enrollment. The magnitude indicates a reduction of over one third of the capitalization effects in the period studied. In 2015-2024, the capitalization effects in districts with no open enrollment also declined by about 1.8%. [6] Nevertheless, in this extended time frame it remains the case that the capitalization effects decreased relatively

[6]Figure 3 suggests that most of the declines for districts with no open enrollment occurred after COVID.

more in districts with open enrollment, compared to districts with no open enrollment, by a magnitude of about 1.6%.

Table 2: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment (Dependent Variables are Log Housing Prices adjusted for Inflation)

	Dependent variable:	
	Log Real Price	
	2010-2019	2010-2024
	(1)	(2)
Quality	0.045***	0.049***
	(0.005)	(0.006)
Quality × OE Switcher	0.005	0.005
	(0.007)	(0.008)
Quality × Post 2014	−0.008*	−0.018***
	(0.005)	(0.004)
Quality × OE Switcher × Post 2014	−0.017***	−0.016***
	(0.006)	(0.006)
Boundary-Year FE?	Yes	Yes
Observations	516,920	818,115
R^2	0.859	0.847

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The DiD coefficient δ_4, which captures the additional decline in the capitalization effect in the post-2014 period in districts districts switching to open enrollment from 2012 to 2025, is bolded. The dependent variable is log housing prices adjusted by inflation. Column 1 analyzes the period 2010 to 2019, and Column 2 analyzes the period 2010 to 2024. Standard errors are clustered at the census block group level.

In order to show that the decline is attributed to school quality, rather than unobserved characteristics correlated with school quality, I examine the same specifications in areas with more parents versus fewer parents from 2010-2024. In theory, buyers who are not parents are less likely to view local school quality as an amenity. Using the merged L2 demographic information, I calculate the fraction of buyers in a given boundary buffer zone who have children. The median value in the sample is about 0.31, suggesting the median neighborhood has 31% of buyers with children. I divide the sample into above median and below median, corresponding to higher fraction of parents and lower fraction of parents in the buyer population, respectively. The mean fraction of parents is 38% in the above median group and 24% in the below median group. Based on results reported in Table 3, I find that in the sample with higher fraction of parents, the baseline capitalization effect is significantly larger, 6.3% compared with 3.5% in the sample with lower fraction of parents. In addition, the decline in the capitalization effect is larger, a 2.2% relative decline for districts that switch to open enrollment in the sample with above median fraction of parents, whereas the relative decline is merely 0.9% in areas with below median fraction of parents.

Turning to the districts which adopted open enrollment early on, the Diff-in-Diff analyses show that they experienced a decline in the capitalization effects in 2010-2014, consistent with the fact that they adopted open enrollment early on. The magnitude is similar to the case of open enrollment switchers, a 2.5% decrease. The capitalization effects for areas with higher fraction of parents decreased more in 2010-2024 by 3.4%, compared with areas with lower fraction by 1.9%.

Taken together, these findings suggest that open enrollment weakened the relationship between housing prices and local school quality. The relationship is weakened to a greater extent in areas with a larger percentage of parents with children.

Table 3: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment (Dependent Variables are Log Housing Prices adjusted for Inflation)

	Dependent variable:		
		Log Real Price	
	2010-2024 All Sample	Above Median Parent Fraction	Below Median Parent Fraction
	(1)	(2)	(3)
Quality	0.049***	0.063***	0.035***
	(0.006)	(0.008)	(0.007)
Quality × OE Switcher	0.005	0.002	0.007
	(0.008)	(0.010)	(0.010)
Quality × Post 2014	−0.018***	−0.025***	−0.009
	(0.004)	(0.006)	(0.006)
Quality × OE Switcher × Post 2014	−0.016***	−0.022***	−0.009
	(0.006)	(0.008)	(0.008)
Boundary-Year FE?	Yes	Yes	Yes
Observations	818,115	409,025	408,193
R^2	0.847	0.850	0.792

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The DiD coefficient δ_4, which captures the additional decline in the capitalization effect in districts switching to open enrollment from 2012 to 2025, is bolded. The dependent variable is log housing prices adjusted by inflation. Column 1 analyzes all samples from 2010 to 2024, Column 2 analyzes boundaries where the fraction of buyers with children is above median from 2010 to 2024, and Column 3 analyzes boundaries where the fraction of buyers with children is below median from 2010 to 2024. Standard errors are clustered at the census block group level.

Table 4: DiD Analyses on Districts Adopting Open Enrollment Early and Districts with No Open Enrollment (Dependent Variables are Log Housing Prices adjusted for Inflation)

	Dependent variable:	
	Log Real Price	
	2010-2019	2010-2024
	(1)	(2)
Quality	0.045***	0.049***
	(0.006)	(0.006)
Quality × OE Early Adopter	−0.025*	−0.025*
	(0.013)	(0.013)
Quality × Post 2014	−0.007	−0.017***
	(0.005)	(0.004)
Quality × OE Early Adopter × Post 2014	−0.007	−0.006
	(0.013)	(0.012)
Boundary-Year FE?	Yes	Yes
Observations	267,060	427,994
R^2	0.874	0.862

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The row name for coefficient δ_3, which captures the difference in the capitalization effect in the pre-2015 period in districts adopting open enrollment early by 2012, is italicized. The dependent variable is log housing prices adjusted by inflation. Column 1 analyzes the period 2010 to 2019, and Column 2 analyzes the period 2010 to 2024. Standard errors are clustered at the census block group level.

Table 5: DiD Analyses on Districts Adopting Open Enrollment Early and Districts with No Open Enrollment (Dependent Variables are Log Housing Prices adjusted for Inflation)

	Dependent variable:		
		Log Real Price	
	2010-2024 All Sample	Above Median Parent Fraction	Below Median Parent Fraction
	(1)	(2)	(3)
Quality	0.049^{***}	0.062^{***}	0.036^{***}
	(0.006)	(0.008)	(0.007)
Quality × OE Early Adopter	-0.025^{*}	-0.034^{**}	-0.019
	(0.013)	(0.015)	(0.024)
Quality × Post 2014	-0.017^{***}	-0.025^{***}	-0.010
	(0.004)	(0.006)	(0.006)
Quality × OE Early Adopter × Post	-0.006	-0.011	0.005
	(0.012)	(0.013)	(0.024)
Boundary-Year FE?	Yes	Yes	Yes
Observations	427,994	213,070	213,941
R^2	0.862	0.868	0.788

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The row name for coefficient δ_3, which captures the decline in the capitalization effect in the early pre-2015 period in districts adopting open enrollment early by 2012, is italicized. The dependent variable is log housing prices adjusted by inflation. Column 1 analyzes all samples from 2010 to 2024, Column 2 analyzes boundaries where the fraction of buyers with children is above median from 2010 to 2024, and Column 3 analyzes boundaries where the fraction of buyers with children is below median from 2010 to 2024. Standard errors are clustered at the census block group level.

5 Residential Sorting

As open enrollment improves the effective school quality of neighborhoods that are assigned to lower quality schools, these neighborhoods may attract home buyers of different demographic characteristics than before. I examine three different types of buyer characteristics, annual household income, bachelor's completion rate and racial composition.

I use the same Diff-in-Diff specification as above, controlling for housing and neighborhood characteristics as well as boundary-year fixed effects. However, instead of controlling for time-varying neighborhood characteristics, I control for neighborhood characteristics in the earliest period 2010-2014, because otherwise the time-varying controls will capture part of the demographic changes of new movers into the neighborhoods.

In districts with no open enrollment, a one standard deviation increase in school quality is associated with a \$6,869 increase in the average annual buyer income in 2010-2014. In districts that switched to open enrollment, the sorting on income is stronger, with an additional difference of \$2,058 in the average annual buyer incomes in 2010-2014. The districts with no open enrollment experienced a decline in sorting by about $\$2,930$ after 2015. However, open enrollment switcher districts decreased more, showing an additional decline of $\$1,768$.

The districts that adopted open enrollment early had a smaller buyer income gap of \$378 than districts with no OE in the initial period. Given the difference between open enrollment switchers and districts with no open enrollment before the policy change, it is possible that this small difference masks a reduction that has already occurred. Post 2014, there is an additional reduction in the income disparity among home buyers across attendance boundaries of $\$2,524$ in districts which implemented open enrollment early on, although it is not statistically significant.

The Difference-in-Differences estimates also provide suggestive evidence of increased racial integration across attendance boundary borders.

Table 6: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment (Dependent Variables are Demographic Characteristics of Buyers)

	Dependent variable:			
	Income	Bachelor	White	Black
	(1)	(2)	(3)	(4)
Quality	6,868.512***	0.018***	0.014**	−0.012**
	(802.980)	(0.006)	(0.007)	(0.005)
Quality × Switcher	2,057.702*	−0.011	0.005	0.004
	(1,108.683)	(0.009)	(0.009)	(0.006)
Quality × Post	−2,930.285***	−0.003	0.004	−0.006
	(775.667)	(0.007)	(0.007)	(0.004)
Quality × Switcher × Post	−1,768.041*	0.006	−0.012	0.008*
	(1,060.468)	(0.010)	(0.009)	(0.005)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	505,202	393,148	464,293	464,293
R^2	0.475	0.191	0.307	0.304

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The DiD coefficient δ_4, which captures the additional decline in the capitalization effect in districts switching to open enrollment from 2012 to 2025, is bolded. The dependent variables are household-level average annual income, whether the household has a member with Bachelor's degree or above, whether the household has a member who is White, and whether the household has a member who is Black. Results from Column 1 to 4 show results for each of the four dependent variables in the sample period from 2010 to 2024. Standard errors are clustered at the census block group level.

Table 7: DiD Analyses on Districts Adopting Open Enrollment Early and Districts with No Open Enrollment (Dependent Variables are Demographic Characteristics of Buyers)

	Dependent variable:			
	Income	Bachelor	White	Black
	(1)	(2)	(3)	(4)
Quality	6,652.159***	0.017***	0.013*	−0.010**
	(808.693)	(0.006)	(0.007)	(0.005)
Quality × Early Adopter	−377.573	−0.028	−0.060**	0.002
	(2,717.969)	(0.023)	(0.025)	(0.010)
Quality × Post	−2,924.905***	−0.003	0.004	−0.006
	(777.238)	(0.008)	(0.007)	(0.004)
Quality × Early Adopter × Post	−2,523.768	0.020	0.052*	0.017*
	(2,897.646)	(0.027)	(0.030)	(0.009)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	265,861	204,988	243,692	243,692
R^2	0.517	0.191	0.297	0.326

*p<0.1; **p<0.05; ***p<0.01

Notes: The table shows difference-in-differences estimates of the parameters δ_1, δ_2, δ_3, and δ_4 in equation (4). The row name for coefficient δ_3, which captures the decline in the capitalization effect in the early pre-2015 period in districts adopting open enrollment early by 2012, is italicized. The dependent variables are household-level average annual income, whether the household has a member with Bachelor's degree or above, whether the household has a member who is White, and whether the household has a member who is Black. Results from Column 1 to 4 show results for each of the four dependent variables in the sample period from 2010 to 2024. Standard errors are clustered at the census block group level.

6 Case Study

One limitation of the analyses above is that I do not know the exact years in which the open enrollment policies were implemented in each district. To provide further evidence, I conduct a case study of three school districts for which the years of implementation are known.

The three school districts are the Denver school district in Colorado, the Washington D.C. school district, and the Newark school district in New Jersey. The reforms were implemented in 2014-2015 in Newark, 2014-2015 in Washington D.C., and 2012-2013 in Denver.

I implement a similar regression as above, but define the post period using the school year in which the open enrollment policy was implemented. For example, in Denver, September 2012 is consider the post period, while August 2012 is considered the pre period. Here, I specify the fixed effects accordingly as boundary-school-year fixed effects. I exclude borders with access to high-quality charter or magnet schools, using the same methodology as described above.

I find that post reform, there is 1.6% decrease in the capitalization effects, a magnitude close to the difference-in-differences coefficient in the main analyses.

7 Extension and Robustness

In this section, I estimate the difference-in-differences model for open enrollment switchers and districts with no open enrollment in different settings to extend the analyses or conduct robustness checks.

As an extension, I use school-level test score growth rates constructed by SEDA as the outcome variable rather than test score levels. The growth rate measures have been validated as good approximations of value-added measures using student-level data (DiSalvo & Yu, 2023). The results are reported in Table A5. I find no capitalization of school value-added in housing prices in the baseline period or post-2014 period. This result is consistent with prior research studying Los Angeles (Imberman & Lovenheim,

Table 8: Case Study of Three School Districts where Policy Years are Known

	Dependent variable:
	Log Real Price
Quality	0.035***
	(0.007)
Quality × Post Reform	−0.016***
	(0.005)
Boundary-Year FE?	Yes
Observations	47,928
R^2	0.849

*p<0.1; **p<0.05; ***p<0.01

Notes: The coefficient on Quality × Post Reform captures the decline in the capitalization effect after the open enrollment policy was implemented, is italicized. The analysis sample consists of three school districts: Newark, Washington DC, and Denver. The dependent variable is log housing prices adjusted by inflation. Standard errors are clustered at the census block group level.

2016).

I conduct several robustness checks.

First, I include controls of distances to the borders, as well as its quadratic and cubic terms. Table A6 shows that the DiD coefficients remain similar.

Second, I adopt a 0.25-mile radius for constructing buffer zones, as in Zheng (2022). Table A7 shows similar results with this adjustment.

Third, I assign a randomly generated placebo indicator of whether the districts adopted open enrollment, within the districts which adopted open enrollment to test whether results are explained by spatially correlated unobservables. Table A8 shows that the DiD coefficients are close to zero, suggesting that spatial autocorrelation is not a serious concern.

Fourth, I cluster standard errors at the district level instead of the census block group level. While the estimates become noisier due to fewer clusters, they remain statistically significant at the 5% level for the 2010-2019 sample and at the 10% level for the 2010-2024 sample.

Fifth, I include controls of middle school quality. If middle school attendance zone borders overlap with elementary school attendance zone borders, the discontinuity in middle school quality could lead to over estimates of elementary school quality premium in any given time period. Table A10 shows that the DiD coefficients do not change substantially.

8 Conclusion

Using variation in open enrollment policy adoption across large school districts, this paper shows that districts implementing open enrollment experienced a 1.7 percentage-point decline in the capitalization of neighborhood school quality in housing prices, estimated at 5% in the initial period. The decline is larger in areas with a higher fraction of buyers who are parents, suggesting that the decrease in capitalization effects can be attributed to changes in the quality of schools accessible to parents.

I also find that districts adopting open enrollment experienced a larger decline in the income gap of buyers across higher and lower test score sides of the attendance school boundaries, suggesting that open enrollment can increase neighborhood socioeconomic integration.

Taken together, my findings suggest that open enrollment could mitigate education inequality and income segregation. However, the policy cannot fully eliminate the inequalities.

In further work, I plan to examine the effects of open enrollment on residential segregation. The linked dataset provides another way of measuring racial and socioeconomic segregation at fine geographical levels. I am also interested in studying effect of school choice on district expenditure allocations across schools.

References

Abdulkadiroğlu, A., Agarwal, N., & Pathak, P. A. (2017). The Welfare Effects of Coordinated Assignment: Evidence from the New York City High School Match. *American Economic Review*, *107*(12), 3635–3689.

Abdulkadiroğlu, A., & Sönmez, T. (2003). School Choice: A Mechanism Design Approach. *American Economic Review*, *93*(3), 729–747.

Bayer, P., Ferreira, F., & McMillan, R. (2007). A Unified Framework for Measuring Preferences for Schools and Neighborhoods. *Journal of Political Economy*, *115*(4), 588–638.

Black, S. E. (1999). Do Better Schools Matter? Parental Valuation of Elementary Education. *The Quarterly Journal of Economics*, *114*(2), 577–599.

Black, S. E., & Machin, S. (2011, January 1). Chapter 10 - Housing Valuations of School Performance. In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), *Handbook of the Economics of Education* (pp. 485–519, Vol. 3). Elsevier.

Caetano, G. (2019). Neighborhood sorting and the value of public school quality. *Journal of Urban Economics*, *114*, 103193.

Campos, C., & Kearns, C. (2024). The Impact of Public School Choice: Evidence from Los Angeles's Zones of Choice*. *The Quarterly Journal of Economics*, *139*(2), 1051–1093.

Carroll, J. M., Harris, D. N., Nair, A., & Nordgren, E. (2023). *National Longitudinal School Database* (tech. rep.). National Center for Research on Education Access and Choice.

Chakrabarti, R., & Roy, J. (2015). Housing markets and residential segregation: Impacts of the Michigan school finance reform on inter- and intra-district sorting. *Journal of Public Economics*, *122*, 110–132.

Chung, I. H. (2015). School choice, housing prices, and residential sorting: Empirical evidence from inter-and intra-district choice. *Regional Science and Urban Economics*, *52*, 39–49.

DiSalvo, R. W., & Yu, J. H. (2023). Housing Affordability and School Quality in the United States. *Journal of Housing Economics*, *60*, 101933.

Fahle, E. M., Saliba, J., Kalogrides, D., Shear, B. R., Reardon, S. F., & Ho, A. D. (2024). *Stanford Education Data Archive: Technical Documentation (Version 5.0).* (tech. rep.).

Figlio, D. N., & Lucas, M. E. (2004). What's in a Grade? School Report Cards and the Housing Market. *American Economic Review*, *94*(3), 591–604.

Hoxby, C. M. (2000). Does Competition among Public Schools Benefit Students and Taxpayers? *American Economic Review*, *90*(5), 1209–1238.

Imberman, S. A., & Lovenheim, M. F. (2016). Does the market value value-added? Evidence from housing prices after a public release of school and teacher value-added. *Journal of Urban Economics*, *91*, 104–121.

Monarrez, T., & Chien, C. (2021, September). *Dividing Lines: Racially Unequal School Boundaries in US Public School Systems* (tech. rep.). Urban Institute.

Reardon, S., Fahle, E., Ho, A., Shear, B., Kalogrides, D., Jang, H., Chavez, B., & Saliba, J. (2023). *Stanford Education Data Archive (SEDA).* Stanford Digital Repository.

Reback, R. (2005). House prices and the provision of local public services: Capitalization under school choice programs. *Journal of Urban Economics*, *57*(2), 275–301.

Ring, M. A. K. (2025). Wealth Taxation and Household Saving: Evidence from Assessment Discontinuities in Norway. *The Review of Economic Studies*, *92*(5), 3375–3402.

Tiebout, C. (1956). A Pure Theory of Local Expenditures. *Journal of Political Economy*, *64*(5).

Wigger, C. J. (2025). Persistence and variation of schools as housing amenities. *Regional Science and Urban Economics*, *110*, 104058.

Zheng, A. (2022). The Valuation of Local School Quality under School Choice. *American Economic Journal: Economic Policy*, *14*(2), 509–537.

Appendix

Motivating Model

I present a simple model, modified from Reback (2005) and Caetano (2019) to guide the empirical analyses. Let the flow utility of household i when choosing school attendance zone j within a given school district be the following:

$$U_{i,j} = \theta ESQ_j + \phi P_j + \xi_j + \epsilon_j \quad j = 1, 2, \ldots J$$

Here ESQ_j represents the effective school quality associated with neighborhood j, while P_j denotes the housing prices in neighborhood j. Households tradeoff effective school quality and housing prices. ξ_j represents unobserved neighborhood amenities and ϵ_j is an error term.

Under a traditional public school system, $ESQ_j = SQ_j$, because the neighborhood school is the only public school option. However, under *intra*-district open enrollment, $ESQ_j = E\left[\max\left(SQ_j, \delta_{i1}SQ_1, \delta_{i2}SQ_2, \ldots, \delta_{iJ}SQ_J\right)\right]$ where $\delta_{ij} \in [0, 1]$ represents agent i 's discounting factor to take into account personal preferences and the availability of transfers for school j.

The estimated decline in the valuation of local school quality does not reflect changes in the true willingness to pay parameter $-\frac{\theta}{\phi}$, but rather changes in effective school quality associated with a given neighborhood.

Classification of Districts

Here I provide further information about how I classify districts into whether they have open enrollment. Most school districts which allow for open enrollment provide an online enrollment system or a form which families could access to apply for transfers to other schools. On the other hand, districts which do not allow for open enrollment typically have the following types of statements on their websites:

- The Board considers voluntary reassignment to be appropriate only in rare or exceptional circumstances.
- The superintendent is authorized to investigate and approve transfers between schools.
- Transfers will be granted only in the following circumstances... (followed by conditions such as safety or hardship)

Some districts offer choice for a small set of schools. In these cases, the district is not considered to have open enrollment. Some districts offer programs of schools of choice within a very limited number of options to choose from. These districts are also not considered to have open enrollment.

More Details on Analysis Sample

Cleaning Step	Number of Districts	Number of Attendance Zones
Merge with Attendance Zone Data	250	9,189
Drop districts without 2025 Policy Data	188	7,886
Drop districts with enrollment shares in charter or magnet schools above 5% by 2019	56	1,767

Notes: This table reports the number of districts and attendance zones after each major data cleaning step.

Table A1: Descriptive Statistics

Variable	Early OE Adopter		No OE	
	High Score Side	Low Score Side	High Score Side	Low Score Side
Observation	24,417	22,399	196,671	184,547
Sale price	614,953	571,928	372,408	359,110
(nominal dollars)	(587,690)	(577,898)	(283,178)	(270,217)
House characteristics				
Log square foot	7.53	7.48	7.66	7.63
	(0.42)	(0.43)	(0.41)	(0.42)
Lot size (acres)	0.26	0.26	0.35	0.35
	(0.53)	(0.37)	(0.70)	(0.71)
Number of bathrooms	3.37	3.27	3.70	3.64
	(1.18)	(1.18)	(1.19)	(1.21)
Year built	1,976.87	1,974.44	1,982.02	1,981.34
	(22.58)	(22.99)	(24.90)	(24.84)
Has parking	0.96	0.95	0.67	0.65
	(0.19)	(0.22)	(0.47)	(0.48)
Has basement	0.01	0.01	0.34	0.34
	(0.09)	(0.11)	(0.47)	(0.47)
Number of stories	1.73	1.67	2.12	2.07
	(0.96)	(0.94)	(0.95)	(0.96)
Total rooms	5.60	5.34	5.27	5.06
	(2.30)	(2.27)	(1.60)	(1.57)
School Quality				
SEDA	0.19	-0.29	0.88	0.38
(standardized)	(1.13)	(1.09)	(0.82)	(0.80)
Place attributes				
Median HH income	111,160.61	102,834.35	108,502.04	103,943.97
	(62,535.23)	(59,402.43)	(47,126.27)	(47,112.92)
Percent White	0.58	0.58	0.66	0.65
	(0.24)	(0.24)	(0.22)	(0.23)
Percent with	0.37	0.33	0.44	0.43
bachelor's or higher	(0.25)	(0.24)	(0.21)	(0.21)

Notes: Summary statistics in 2010-2024 for districts which adopted open enrollment early by 2012 (first and second column) and for districts with no open enrollment during this period (third and fourth column). The first and third column reports descriptive statistics for the higher test score side, while the second and fourth column for the lower test score side. The means are present, with standard deviation in the parentheses.

Table A2: Housing Quality Index and Local School Quality

	Dependent variable:	
	Standardized School Quality	
	OE Switcher	OE Early Adopter
	(1)	(2)
Standardized Housing Quality Index	0.018***	0.018***
	(0.003)	(0.003)
Housing Quality Index × OE District	0.008*	-0.006
	(0.004)	(0.008)
Boundary-Year FE?	Yes	Yes
Observations	461,920	232,756
R^2	0.887	0.896

*p<0.1; **p<0.05; ***p<0.01

Notes: The table reports the results of regression of school quality on housing quality index and an interaction term between housing quality index and indicator variable for districts which implemented open enrollment. In the first column, the districts which implemented choice are the districts which switched to open enrollment from 2012 to 2025. In the second, they are the districts which adopted open enrollment early by 2012. The regression captures housing quality differences at different sides of school attendance boundaries.

Table A3: Hedonic Regression Results for Trends in the Capitalization of Neighborhood School Quality in Housing Prices

	Log Real Price	
	OE Switcher	No OE
	(1)	(2)
Quality × 2010	0.090***	0.084***
	(0.005)	(0.005)
Quality × 2011	0.111***	0.101***
	(0.006)	(0.006)
Quality × 2012	0.112***	0.103***
	(0.007)	(0.006)
Quality × 2013	0.094***	0.099***
	(0.005)	(0.005)
Quality × 2014	0.090***	0.100***
	(0.005)	(0.005)
Quality × 2015	0.078***	0.092***
	(0.005)	(0.005)
Quality × 2016	0.065***	0.078***
	(0.005)	(0.005)
Quality × 2017	0.053***	0.067***
	(0.006)	(0.005)
Quality × 2018	0.035***	0.059***
	(0.005)	(0.005)
Quality × 2019	0.026***	0.051***
	(0.005)	(0.005)
Quality × 2020	0.022***	0.039***
	(0.005)	(0.005)
Quality × 2021	0.016***	0.034***
	(0.005)	(0.005)
Quality × 2022	0.020***	0.038***
	(0.005)	(0.006)
Quality × 2023	0.018***	0.034***
	(0.006)	(0.005)
Quality × 2024	0.026***	0.028***
	(0.005)	(0.006)
District-Year FE?	Yes	Yes
Observations	811,223	680,991
R^2	0.766	0.787

Notes: The table reports the results of hedonic regression of housing prices on local school quality interacted with sale year. In the first column, the sample consists of districts which switched to open enrollment between 2012 and 2025. In the second, the sample includes districts with no open enrollment. The regression captures trends in the non-causal relationship between housing prices and local school quality over time.

Table A4: Boundary Discontinuity Results for Trends in the Capitalization of Neighborhood School Quality in Housing Prices

	Log Real Price	
	OE Switcher	No OE
	(1)	(2)
Quality × 2010	0.052***	0.043***
	(0.007)	(0.008)
Quality × 2011	0.058***	0.053***
	(0.007)	(0.007)
Quality × 2012	0.068***	0.048***
	(0.007)	(0.007)
Quality × 2013	0.049***	0.054***
	(0.007)	(0.009)
Quality × 2014	0.048***	0.045***
	(0.006)	(0.008)
Quality × 2015	0.040***	0.058***
	(0.006)	(0.008)
Quality × 2016	0.034***	0.042***
	(0.007)	(0.010)
Quality × 2017	0.028***	0.039***
	(0.006)	(0.007)
Quality × 2018	0.018***	0.030***
	(0.007)	(0.006)
Quality × 2019	0.028***	0.038***
	(0.008)	(0.007)
Quality × 2020	0.013**	0.026***
	(0.006)	(0.006)
Quality × 2021	0.013**	0.019***
	(0.006)	(0.006)
Quality × 2022	0.001	0.019***
	(0.006)	(0.006)
Quality × 2023	0.013*	0.021***
	(0.007)	(0.007)
Quality × 2024	0.015**	0.017**
	(0.007)	(0.007)
Boundary-Year FE?	Yes	Yes
Observations	437,323	381,218
R^2	0.855	0.838

Notes: The table reports the results of boundary discontinuity regression of housing prices on local school quality interacted with sale year. In the first column, the sample consists of districts which switched to open enrollment from 2012 to 2025. In the second, the sample includes districts with no open enrollment. The regression captures trends in the causal relationship between housing prices and local school quality over time.

Table A5: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment, using A Proxy of Value-Added as the Outcome

	Dependent variable:			
	Log Real Price			
	2010-2019	2010-2024	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	−0.002	−0.002	−0.002	−0.001
	(0.003)	(0.003)	(0.004)	(0.005)
Quality × OE Switcher	0.004	0.004	0.005	0.003
	(0.004)	(0.005)	(0.006)	(0.007)
Quality × Post 2014	−0.002	−0.001	0.0002	−0.003
	(0.002)	(0.002)	(0.003)	(0.004)
Quality × OE Switcher × Post	0.006	−0.001	−0.006	0.004
	(0.005)	(0.004)	(0.005)	(0.006)
Observations	464,407	734,424	352,221	381,306
R^2	0.859	0.848	0.852	0.793
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A6: Robustness: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment, Adding Functions of Distances as Controls

	Dependent variable:			
	Log Real Price			
	2019 All	2024 All	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	0.045***	0.049***	0.063***	0.035***
	(0.005)	(0.006)	(0.008)	(0.007)
Quality × OE Switcher	0.005	0.005	0.002	0.007
	(0.007)	(0.008)	(0.011)	(0.010)
Quality × Post 2014	−0.008*	−0.018***	−0.025***	−0.009
	(0.005)	(0.004)	(0.006)	(0.006)
Quality × OE Switcher × Post	−0.017***	−0.016***	−0.022***	−0.009
	(0.006)	(0.006)	(0.008)	(0.008)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	516,920	818,115	409,025	408,193
R^2	0.859	0.847	0.850	0.792

*p<0.1; **p<0.05; ***p<0.01

Table A7: Robustness: DiD Analyses on Districts Switching to Open Enrollment and Districts with No Open Enrollment, using 0.25-mile Buffer Zone

	Dependent variable:			
	Log Real Price			
	2019 All	2024 All	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	0.044***	0.048***	0.061***	0.036***
	(0.006)	(0.006)	(0.009)	(0.007)
Quality × OE Switcher	0.006	0.006	0.003	0.009
	(0.007)	(0.008)	(0.011)	(0.011)
Quality × Post 2014	−0.008*	−0.017***	−0.025***	−0.010
	(0.005)	(0.004)	(0.006)	(0.006)
Quality × OE Switcher × Post	−0.015**	−0.016**	−0.020**	−0.010
	(0.006)	(0.006)	(0.008)	(0.009)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	452,254	715,475	358,608	356,094
R^2	0.862	0.850	0.853	0.796

*p<0.1; **p<0.05; ***p<0.01

Table A8: Robustness: DiD Analyses within Districts Switching to Open Enrollment, using a randomly generated Open Enrollment Policy Indicator

	Dependent variable:			
	Log Real Price			
	2010-2019	2010-2024	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	0.050***	0.055***	0.069***	0.039***
	(0.005)	(0.005)	(0.006)	(0.008)
Quality × OE Switcher	−0.001	−0.001	−0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.003)
Quality × Post 2014	−0.024***	−0.033***	−0.047***	−0.016***
	(0.004)	(0.004)	(0.006)	(0.006)
Quality × OE Switcher × Post	−0.002	−0.001	0.001	−0.006
	(0.002)	(0.002)	(0.002)	(0.004)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	281,858	437,323	225,071	212,000
R^2	0.863	0.855	0.862	0.802

*p<0.1; **p<0.05; ***p<0.01

Table A9: Robustness: DiD Analyses within Districts Switching to Open Enrollment, Clustering Standard Errors at the District Level

	Dependent variable:			
	Log Real Price			
	2010-2019	2010-2024	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	0.045***	0.049***	0.063***	0.035***
	(0.007)	(0.007)	(0.015)	(0.007)
Quality × OE Switcher	0.005	0.005	0.002	0.007
	(0.011)	(0.012)	(0.020)	(0.012)
Quality × Post 2014	−0.008	−0.018***	−0.025**	−0.009
	(0.006)	(0.005)	(0.009)	(0.006)
Quality × OE Switcher × Post	−0.017**	−0.016*	−0.022*	−0.010
	(0.009)	(0.009)	(0.012)	(0.009)
Boundary-Year FE?	Yes	Yes	Yes	Yes
Observations	517,127	818,541	409,080	408,563
R^2	0.859	0.847	0.850	0.792

*p<0.1; **p<0.05; ***p<0.01

Table A10: Robustness: DiD Analyses within Districts Switching to Open Enrollment, including Middle School Quality as a Control

	Dependent variable:			
	Log Real Price			
	2010-2019	2010-2024	Above Median	Below Median
	(1)	(2)	(3)	(4)
Quality	0.041***	0.044***	0.056***	0.033***
	(0.006)	(0.006)	(0.009)	(0.007)
Quality × OE Switcher	0.005	0.006	0.006	0.005
	(0.007)	(0.008)	(0.011)	(0.011)
Quality × Post 2014	−0.006	−0.016***	−0.024***	−0.007
	(0.005)	(0.004)	(0.006)	(0.006)
Quality × OE Switcher × Post	−0.017***	−0.017***	−0.024***	−0.009
	(0.006)	(0.006)	(0.008)	(0.008)
Observations	488,637	772,665	382,193	389,628
R^2	0.861	0.850	0.852	0.791
Note:				*p<0.1; **p<0.05; ***p<0.01