Tracking the Housing Price Premium in Shanghai Middle School Districts from 2015 to 2021

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I. Introduction

Soaring house prices in China have long been a focal point of research by economists. Fang et al. (2016) discovered approximately 13% yearly real growth rate of housing prices in first-tier Chinese cities from 2003 to 2013. According to Li et al. (2019), in Shanghai the typical unit transaction price of resale apartments surged from 19,810 to almost 52,140 yuan from 2009 to 2016, and the real growth rate was about 112.41%; however, the inflation-fixed growth rate of income per capita in Shanghai was just 51.97%. This far slower growth rate of income relative to housing prices is liable to aggravate issues such as poor housing affordability, the crowding out of high-end labor (Jeanty et al., 2010), the obstruction caused to the growth of industries apart from real estate (Han et al., 2021), and so on. Given these side effects, it is especially critical to discover the factors that are driving up China's housing price. Prior research has attributed the rise in housing price to various factors including educational amenities (Wen et al., 2014), advancement of public transport (Xiao et al., 2017), the distance to the central business area (e.g., Chen & Hao, 2008), and net migration (Chen et al., 2011).

This research proposal aims to study the effect of educational amenities on housing price in China by appraising the housing price premium connected to quality middle school education in Shanghai. Particularly, this research proposal looks at such premium subsequent to three policies being put into effect, namely, the nearby school policy initiated by the Chinese national government in 1986 and implemented in Shanghai by the end of 2014, the 2020 middle school admission reform executed by Shanghai Municipal Education Commission (SMEC), and the 2022 high school admission reform recently announced by SMEC. The nearby school policy has allocated every household to a specific school district according to their residential address. Consequently, children will automatically be assigned to the public middle school located in their respective school district. School district housing near high quality middle schools is thus anticipated to have a price premium in comparison with those close to ordinary middle schools. In the meantime, as introduced in Section II, the two policies announced by SMEC are anticipated to impact the education premium to a certain degree by impacting the demand side, i.e., a household's willingness to procure school-district housing.

The study chooses Shanghai as the object of study because: 1) Shanghai is a worldwide cosmopolitan city with a continuously rising population growth rate and a skyrocketing housing price. These two aspects may engender geographic discrimination that possibly jeopardizes Shanghai's sustainable development; 2) Shanghai is one of the first cities to implement provincial education policies that might cause instability to the housing price premium connected to quality education. Comprehending whether the policies are influencing housing prices in a positive or negative way will assist government authorities in Shanghai and other cities to create policies that could successfully decrease burdens on (prospective) homeowners in China.

Hence, using web-scraped data mostly from Lianjia, SMEC, Fang.com, and Gaode Map, this research paper intends to comprehend the subsequent questions:

(1) What is the housing price premium connected to high quality public middle schools after the nearby school policy was initiated in Shanghai by the end of 2014?

(2) How has the realization of the 2020 middle school admission reform affected this premium?

(3) How has the publication of the 2022 high school admission reform affected this premium?

As discussed in detail in Section III, the major contribution of this research is twofold. Firstly, prior research on school quality and housing price in China only looked into the primary school education premium, while this paper means to appraise middle school education premium. Secondly, since the two admission reforms were implemented extremely recently, this paper is the first to scrutinize the outcome of the two education policies on Shanghai's housing prices. Other cities such as Beijing and Hangzhou (Lin & Zheng, 2021;

Zhao & Cao, 2020) are also gradually implementing policies that are similar to the 2020 and 2022 admission reforms in Shanghai, so the outcome of this study will not only have provincial implications, but also national implications, as these reforms signify the national government's effort to attain "common prosperity" by equalizing the access of educational resources to households of various tiers of wealth and power.

That said, this research proposal is structured as follows: Section II introduces China's education system and the education policies pertinent to the current study; Section III reviews the relevant literature this study has referred to; Section IV briefly illustrates the identification strategy of this research proposal; Section V presents the data used; Section VI offers observational results; Section VII discusses the next steps to take to advance this study; Section VIII concludes the research proposal.

II. Background

1. School District Housing and the Nearby School Policy

Xue Qu Fang, or school district housing, is the outcome of China's key public school system, the nearby school policy of 1986, and the mushrooming real estate market in the prior decade. In 1953, Politburo of the Chinese Communist Party propounded the concept of "key public schools", which, evaluated against common public schools, ought to excel in both academic reputation and the quality and quantity of educational resources allocated by the state (Chen & Shi, 2018). Politburo contended that provincial governments ought to institute a sensible number of key public schools in order to teach talents to contribute to China's technological advancement and modernization. As a result, more than 7000 primary schools and 5200 middle schools had been designated across the nation as key schools by 1979 (Gu, 2000). Even though the original reason for suggesting such a stratified structure was to consolidate academic resources to accelerate China's development, the presence of key schools produced an unequal distribution of academic opportunities between the rich and the poor. Questions were asked concerning whether these public schools had favored students from more educated and wealthy households. Furthermore, it was reported that key schools had accepted students whose parents were government officials in exchange for funding, (Wang, 2014).

To deal with these issues, the Compulsory Education Law of the People's Republic of China of 1986 declared the nearby school policy, which mandated that public schools (both primary and middle schools) ought to start admitting students by looking at the distance between the student's registered residence – *Hukou* – and the school (Han et al., 2021). Nonetheless, since educational disparity between key schools and ordinary schools continues, parents have tried to purchase houses in designated school attendance zones as a way of sending their children to key public schools. School district houses, referring to houses located in zones assigned with (usually prestigious) public primary or middle school(s), have developed into a derivative product in China's real estate market. It is calculated that school district houses near high-quality primary schools were sold at an average premium of about 11% from 2013 to 2016 in Beijing (Han et al., 2021) and roughly 14% from 2015 to 2016 in Shanghai (Chan et al., 2020).

2. Regional Policy Shocks on School District Housing

Subsequent to the nearest enrollment rule being implemented by the national government, SMEC initiated two local policies to ensure a more even allocation of educational resources and student quality across schools. Therefore, the period from 2014 to 2021 saw three exogenous policy shocks in Shanghai: the nearby school policy that was implemented by the Ministry of Education of China (MOE) in 2014 (MOE, 2014), the 2020 middle school admission reform announced by SMEC in March 2020 and put into practice in April (SMEC, 2020), and the latest 2022 high school admission reform declared by SMEC in March 2021 (SMEC, 2021).

As exhibited in Figure 1 and Figure 2, the main alteration made by the 2020 middle school admission reform was to limit students from applying to private schools whilst taking advantage of the nearby school policy. Preceding the policy change, students who applied to private schools were given the choice of attending a public school through the nearby school policy if their selected private schools rejected them.

However, effective from April 2020, if a student opts to apply to a private school, they will automatically forgo the chance to enroll in a nearest public school, regardless of the admission result from the private school. Students who have failed to gain admission into a private school will be entered into a computer-generated process that quasi-randomly assigns them to a public middle school based on how many available slots are left. The quality of those public middle schools assigned using this process cannot be assured.

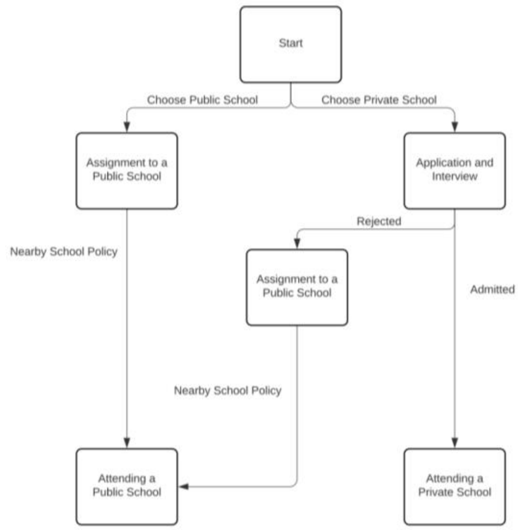

Figure 1. Middle School Admission Procedure Prior to 2020 Admission Reform

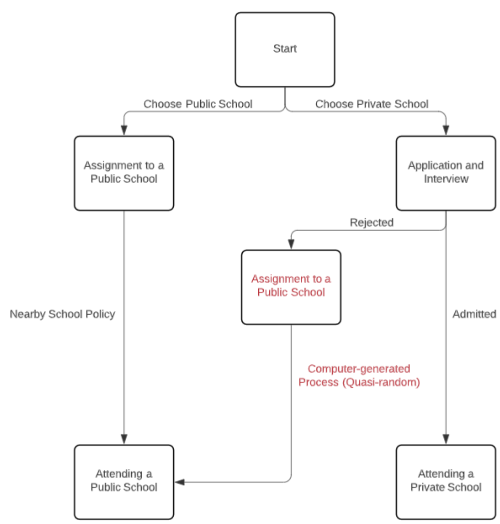

Figure 2. Middle School Admission Procedure Post 2020 Reform

One would anticipate such an admission modification to have a stratified impact on parents' decisions to purchase school district housing. Table 1 reveals the number of quality middle schools in Shanghai. The table shows only tier-1 and tier-2 schools amongst the four tiers classifying Shanghai middle schools. Amongst the schools ranked as top 10 in education quality in Shanghai, 8 are private schools. Nevertheless, the entire number of public schools in tier-1 is similar to that of private schools, while the number of public schools in tier-2 is over double that of private schools in the same tier. Similarly, the entire number of quality public middle schools is above that of private middle schools. This suggests that while the best schools in Shanghai are typically private schools, public schools are still a majority of the high-quality middle schools in the city. Consequently, one might anticipate wealthy or powerful households with children of outstanding academic performance to risk choosing the private-school-track, while regular households with children of average or below-average academic performance to take advantage of the nearby school policy by acquiring houses close to key public schools. It is likely that the former group will assign a lower utility to acquiring school district housing, while the latter group is predicted to act the opposite. The collective impact on housing price in school districts is thus dependent on the degree to which the two effects offset each other.

	Tier 1	Tier 2	Tier 1 & Tier 2 Total	Top 10
# Total Public Schools	28	37	65	2
# Total Private Schools	23	16	39	8

Table 1. Number of Quality Public and Private Middle Schools[1]

Meanwhile, the 2022 high school admission reform stated that about 50% - 65% of the admission decisions in public high schools ought to be based on a ranking mechanism at a district level or a school level. Particularly, each public high school administered by districts ought to admit a specific number of top students from every public middle school within its own district ("school-wise admission through

[1] Source of reference is Shanghai Xuekao, which is one of the most commonly used social networking platforms for schooling information.

allocation") and a specific number of top students from every district ("district-wise admission through allocation"), not giving any consideration to the general education quality of the school or the district. If the public high school is administered directly by the Shanghainese government, then its school-wise admission via allocation randomly applies to a set of public middle schools in Shanghai. Table 2 summarizes the percentages allocated to each admission process before and after the 2022 admission reform.

Admission Processes			Admission through Application	Admission through Allocation (district-wise)	Admission through Allocation (school-wise)	Admission through Entrance Exam
Prior to 2022	Percentage of Students Admitted	Key Schools Administered by Shanghai	~100%	0%	0%	~0%
		Key Schools Administered by Districts	55%	0%	15%	30%
		Non-key schools Administered by Districts	20%	0%	0%	80%
Effective from 2022	Percentage of Students Admitted	Key Schools Administered by Shanghai	15%-35%	52%[1]	13%[2]	0-20%
		Key Schools Administered by Districts	15%	15%-19.5%[3]	35%-45.5%[4]	20%-35%
		Non-key schools Administered by Districts	15%	0%	0%	85%

[1] The percentage of admission per district is weighted by the number of candidates per district.
[2] Schools administered directly by Shanghai will randomly select a set of public middle schools to allocate slots of enrollment.
[3] Slots will be allocated to every district in Shanghai.
[4] Slots will be allocated to every school in the district of administration.

Table 2. High School Admission Policy Pre and Post 2022 Reform

Taking into consideration the expected positive relationship between admission to quality middle schools and admission to quality high schools, the policy modification offers students who do not live in school districts near key public middle schools a greater probability of attending a quality high school in their administrative districts, at the very least. Therefore, the 2022 reform is likely to enforce a negative spillover effect on the housing premium in key middle school districts.

3. Complications on Shanghai's Nearby School Policies for Middle Schools

The major focus of this study is the housing price premium of public middle schools in Shanghai. While allocation to public primary schools follows the nearby school policy strictly for all districts in Shanghai, this is not entirely the case for middle schools. Amongst the 16 administrative districts in Shanghai, 9 districts assign students to public middle schools based strictly on their residential location, while 4 districts assign students based strictly on where the students attended their primary schools. The remaining 3 districts – Xuhui, Jing'an, and Changning – have a one-to-one matching between primary schools and middle schools for some of their primary schools and a one-to-many matching for the rest. In the latter case, a primary school student will be indiscriminately matched to a public middle school by a computer-generated process.

III. Literature Review

1. Research on Residential Sorting

This study belongs to a strand of literature that primarily stems from Tiebout (1956), in which the author instituted a theoretical model that predicts residential sorting. His model predicts that housing prices in equilibrium are contingent on the preferences of the local residents who have opted to live in the relative areas due to the desired quality of local public goods such as schooling.

Subsequent to Tiebout (1956), McFadden (1973; 1978) developed a random utility model to transform the theory of economic choice behavior into models on households' residential location choices. Since then, a flow of research papers estimated household preferences for neighborhoods utilizing discrete-choice models, a subset of which particularly estimated household preferences for school quality of neighborhoods (Quigley, 1985; Nechyba & Strauss, 1998; Barrow, 2002).

While the discrete-choice model restricted the residential selections of households into a finite set, a different set of literature (e.g., Rosen, 1974; Epple, 1987; Nesheim, 2001; Ekeland et al., 2004) used hedonic demand models that can be utilized to estimate demand on nonmarketed goods through allowing households to choose their optimal level of consumption. This dichotomy afterwards led to Bayer et al. (2007), in which the authors established an integrated framework using both the hedonic demand model and the traditional discrete-choice models. The major empirical accomplishment of Bayer et al. (2007) will be discussed in the subsequent subsection.

2. Research on School Quality and Housing Prices

A thread of empirical research has investigated the impact of school quality on housing prices in equilibrium. Black (1999) conducted a study of great econometric importance by ascertaining the endogeneity caused by variation in neighborhood quality. More precisely, top quality schools are apt to be located in quality neighborhoods, the latter of which also helps establish housing prices. To remove omitted variable bias, Black (1999) proposed a boundary discontinuity design that limited the sample of study to houses on the boundary of school districts. This method successfully removed bias caused by neighborhood characteristics. Using a sample of homeowners in suburban Boston, Black (1999) discovered that parents' marginal willingness-to-pay increased by 2.1 percent as elementary test scores increased by one standard deviation.

Nevertheless, a possible concern for the boundary discontinuity method is that households of dissimilar demographic characteristics could sort across boundaries. To account for such varying sociodemographic characteristics at the two sides of the boundary, Bayer et al. (2007) used a regression discontinuity method while controlling for the demographic characteristics of households (such as races) in the neighborhoods and discovered that doing so appreciably decreased the education premium. Bayer et al. (2007) also used a structural equation model to approximate mean marginal willingness-to-pay when households are heterogenous. They established that the outcome from the structural equation sorting model is extremely close to the one from the hedonic price regression. Generally speaking, their research on households in San Francisco proposes that a one-standard-deviation increase in test score increases mean marginal willingness-to-pay by 1%.

Other empirical research of this area includes Gibbons & Machin (2003; 2006), Davidoff and Leigh (2008), Fack & Grenet (2010), and Gibbons et al. (2013). These studies conducted their research using European and Australian data and they all found positive housing price premiums connected to quality schools. Amongst these studies, Fack & Grenet (2010) used a cross-boundary differential model to control for unobserved neighborhood traits that might differ considerably around the boundaries.

3. Research on School Quality Premiums in China

A small amount of research has paid attention to school quality and housing price in China (Zheng et al., 2015; Zhang & Chen, 2018; Chan et al., 2020; Han et al., 2021). Zheng et al. (2015) found that a premium of 8.1% was connected to housing prices in the attendance zone of key primary schools in Beijing in 2011. Zhang & Chen (2018) found that such a premium for key primary schools in Shanghai was about 6.5% between 2013 and 2014. Since the two studies classified schools using a categorical structure (e.g., "key primary school" vs. "non-key primary schools"), Chan et al. (2020) added to the research on primary school premium in Shanghai by using continuous measures on school quality, including measures such as tournament performance, student-to-teacher ratio, etc. They also controlled for unobserved neighborhood attributes using average rent per neighborhood, realizing that rent reflects neighborhood quality, but not access to education. They discovered a premium of 14% for housing close to primary schools they rated as above the 90th percentile between 2015 and 2016.

A drawback of the studies on China thus far is that they all used data over a somewhat short time span, so they did not explain the trend of premium over time or alterations in school attendance zones. Han et al. (2021) thus increased the time span to 3 years for Beijing primary schools, from 2013 to 2016, finding an average premium of 11% and an increase in premium over time. In addition, they discovered that an upgrade in school attendance zone quality could possibly increase housing price by 1.5% to 3.5%.

That said, this paper's main contribution to the existing literature of the field is that it examines housing price premium connected to public middle schools in Shanghai, China, which no existing literature has done. Prior literature on China has looked only at primary school premiums, but public middle school assignments also abide by the nearby school policy to some extent, which provokes premium on school district housing. Note that the school regions of public middle schools are different from those for primary schools. This paper also studies the two latest policy shocks that influence residential sorting and equilibrium housing prices. Doing so allows this research to evaluate the policy outcomes of local Shanghainese government (following the broader tactics of the national government) who meant to equalize education resources across areas. As far as this paper is concerned, no research on China thus far has studied such policy impacts.

Similar to Han et al. (2021), this study spans a time period of 7 years, making feasible the assessment of trends in premium. Nonetheless, due to time constraints, this research paper has not yet gathered data to account for local demographic characteristics and other unobserved neighborhood traits. This paper also has not gathered data for continuous measures on school quality. These data restrictions will be dealt with later and potential steps on data compilation and evaluation strategies will be mentioned.

IV. Empirical Strategy

To estimate the annual housing price premiums associated with quality school districts, this research proposal employs a hedonic price regression with boundary discontinuity design for each year in the sample. One aim of such a method is to elicit a direct estimate of housing price premiums associated with quality school districts. Another aim is to observe if the two policy shocks resulted in significant patterns of change in housing price premiums. Since the result cannot be fully causal, the study will apply a triple difference-in-difference with boundary discontinuity design in the future when control group data are available. The strategy for a triple difference estimator is illustrated in Section VII.

1. Boundary Discontinuity Identification (BDD)

This section simply presents how regression discontinuity can be used in a geographic context. The BDD identification procedure is adapted from Hahn et al. (2001).

Consider a random, independent and identically distributed cross-sectional sample of housing units $i \in \{1, 2, \dots, n\}$. The running variable for housing unit *i* is D_i, which presents a housing unit's distance to school boundary. A positive sign is assigned to the measured distance if the housing unit *i* is within the key school district, and a negative sign is assigned if house *i* is outside the key school district. The treatment variable is therefore $T_i = \mathbf{1}(D_i \geq 0)$, and the observed outcome for *i* is:

$$y_i = f(D_i) + \tau(D_i)\mathbf{1}(D_i \geq 0) + X_i\Upsilon + u_i \ (1)$$

where $f(D_i)$ entails geographic variables that could influence the outcome (i.e., housing price) such as proximity to the city center and local amenities, and $\varepsilon_i \equiv X_i\Upsilon + u_i$ contains both observed and unobserved individual characteristics that could affect the housing price. Then the average treatment effect at D_i is $Y_i(1) - Y_i(0) = \tau(D_i)$.

The two assumptions for boundary discontinuity are:

Assumption 1: $f(D)$ and $\tau(D)$ are continuous at $D = 0$.

Assumption 2: $\mathrm{E}[\varepsilon_i | D_i = D]$ is continuous at $D = 0$.

For variable *v*, define $v^+ \equiv \lim_{D_i \to 0^+} v_i$ and $v^- \equiv \lim_{D_i \to 0^-} v_i$. Under **Assumption 1** and **Assumption 2**:

$$y^+ - y^- = f^+ + \tau(D_i)^+ + \varepsilon^+ - f^- - \varepsilon^- = f^+ - f^- + \varepsilon^+ - \varepsilon^- + \tau(0) = \tau(0) \ \ (2)$$

Hence, when the two assumptions are satisfied, houses within the school attendance zones near the boundary identify $f(0) + \tau(0)$ and houses outside the school attendance zones near the boundary identify $f(0)$. Then, taking the difference between the two will identify $\tau(0)$.

2. Hedonic Price Regression with BDD

Using BDD as illustrated, this research proposes the use of a simple reduced-form, hedonic price regression. Although, if time permits, a structural equation model (see Bayer et al., 2007) can be applied, hedonic price regression is still extremely useful in the empirical evaluation of housing price premiums when adequate control variables are included. A standard hedonic price model with a dichotomous school quality classification follows:

$$ln(p_{i,n,t}) = \alpha_t + \beta key_{it} + X_{it}\Upsilon + K_{nt}\delta + \varepsilon_{i,n,t} \quad (3)$$

where $ln(p_{i,n,t})$ is the logarithm of real price of housing unit *i* located in neighborhood *n* at time *t*. key_{it} is a dummy variable of whether the household is located in a school attendance zone with a quality school at time *t*, X_{it} is a time-variant vector of individual housing characteristics, K_{nt} is a time-variant vector of neighborhood characteristics (including neighborhood and socio-demographic attributes), α_t is the time fixed effect, and $\varepsilon_{i,n,t}$ is the error term that accounts for any other idiosyncrasy that affects housing price. Our particular point of interest is β, which reflects the mean marginal willingness-to-pay of households for assignments to nearby quality schools. For the boundary discontinuity method, the sample used in this study is further limited to households that are located around the school district boundaries. As $\varepsilon_{i,n,t}$ might contain unobserved neighborhood attributes that affect housing prices, a boundary-fixed-effect approach is applied to the hedonic price regression. Thus, each housing unit *i* at time *t* is matched to its closest boundary, as influenced by SMEC's assignment strategy at time *t*. Then, a set of time-variant boundary dummies – $\theta_{bt} -$ is included into the regression to obtain:

$$ln(p_{i,n,t}) = \alpha_t + \beta key_{it} + X_{it}\Upsilon + K_{nt}\delta + \theta_{bt} + e_{i,n,t} \quad (4)$$

where $e_{i,n,t}$ is the error term in this model. The boundary dummies can reflect the unobserved neighborhood characteristics of households – whether inside or outside the school attendance zones – that are near and share the same boundary. The standard error is clustered at the school district level to address the spatial correlations of unobserved traits between housing units within a school district. Since preliminary results are being estimated, this regression does not include polynomials of distance-to-boundary measures. In the future, this study can use polynomials to control for spatial price trends around boundaries (see Chan et al., 2020).

V. Data

1. Housing Transaction Data

Data on 280,831 resale housing transactions from January 2015 to December 2021 were gathered from Lianjia, one of the largest real-estate agencies in China. These transaction records include details of housing-level information: price, price per square meter, number of bedrooms, address, internal conditions, and the like[2]. Geographic coordinates were obtained through inputting the residential addresses on Gaode Map. Figure 3 and Table 3 show the data points distributed across the 16 administrative districts of Shanghai.

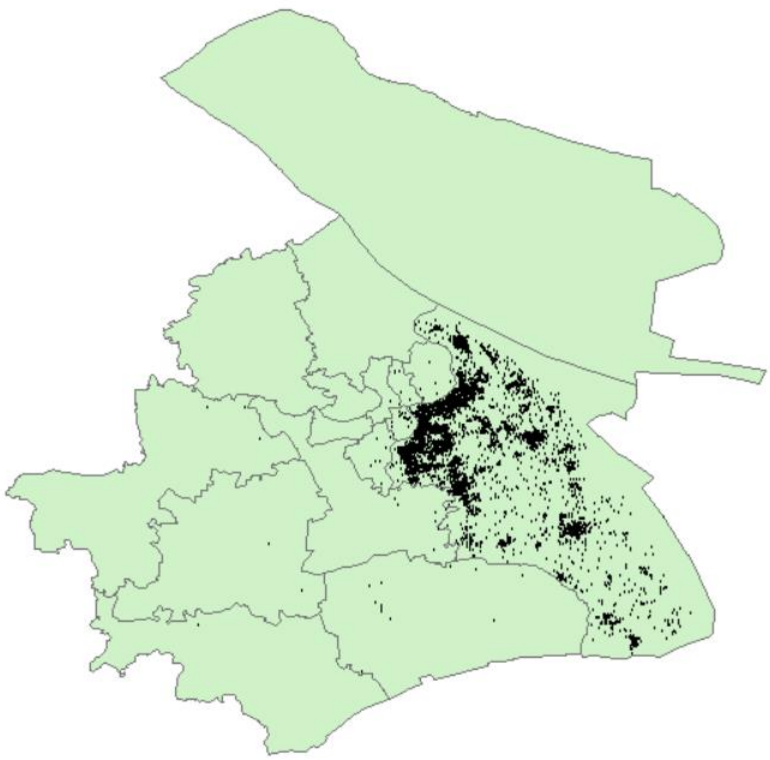

Figure 3. Distribution of Transaction Records in Shanghai

[2] Ziying et al. (2019) discovered that resale housing price above a certain threshold will be downwardly misreported to avoid business tax. According to a manager from Lianjia, transaction price is expected to be 15% - 20% lower than the actual transaction price because of dual contract.

Figure 3 shows that most data points center around the central business district, which is at the border adjacent to Xuhui, Luwan, Huangpu, and Pudong. Table 3 shows that nearly 25% of the data points are from Pudong, which boasts exceptional education resources for both private and public schools. Unlike districts such as Yangpu and Xuhui, where private schools are considered better than public schools, the quality of private and public schools are generally similar to each other in Pudong. Therefore, buying a house in Pudong is considered desirable for households that would like to live close to a quality private middle school whilst taking advantage of the nearby school policy.

Due to time constraints and the computationally extensive requirements for spatial data processing, this research proposal focuses on Pudong district as a sample for the hedonic price regression. Pudong is selected because it occupies a high percentage of the sample and provides access to exceptional education services that induce purchasing of housing in school district areas. Moreover, Pudong qualifies as a sample to test for the regression because it strictly abides by the nearby school policy for middle schools, where each residential address is assigned to one public middle school nearby.

District	Frequency	Percent
Other	1	0
Jiading	15,808	5.63
Fengxian	7,749	2.76
Baoshan	26,050	9.28
Chongming	40	0.01
Xuhui	18,329	6.53
Putuo	19,361	6.89
Yangpu	16,830	5.99
Songjiang	18,294	6.51
Pudong	66,146	23.55
Hongkou	8,376	2.98
Jinshan	870	0.31
Changning	14,626	5.21
Minhang	37,110	13.21
Qingpu	6,895	2.46
Jing'an	15,700	5.59
Huangpu	8,646	3.08

Table 3. Frequency Table of Transaction Records across Districts

Figure 4 plots changes in annual real housing prices (base year: 2016) from January 2015 to December 2021 in Shanghai. The blue line presents the average housing price per month in the sample, and the shaded area presents the 95% confidence interval. The red line presents the average housing price per month for existing houses according to data from the National Bureau of Statistics of China (Note: data from 2020 to 2021 are not available). The dashed red lines indicate the time-points of two regional policies – the 2020 admission reform and the 2022 admission reform – in order.

Since most of the sample data points are located in high-priced areas, the real housing price in the sample is about 20,000 to 40,000 yuan/square meter higher than the Shanghai average. Figure 5 shows that the average housing price in Pudong follows a trend similar to the overall trend in the full sample, but with higher prices on average. At the same time, although with fluctuation, the average housing price in Shanghai – in this sample and from the National Bureau of Statistics – indicates an increasing trend over time.

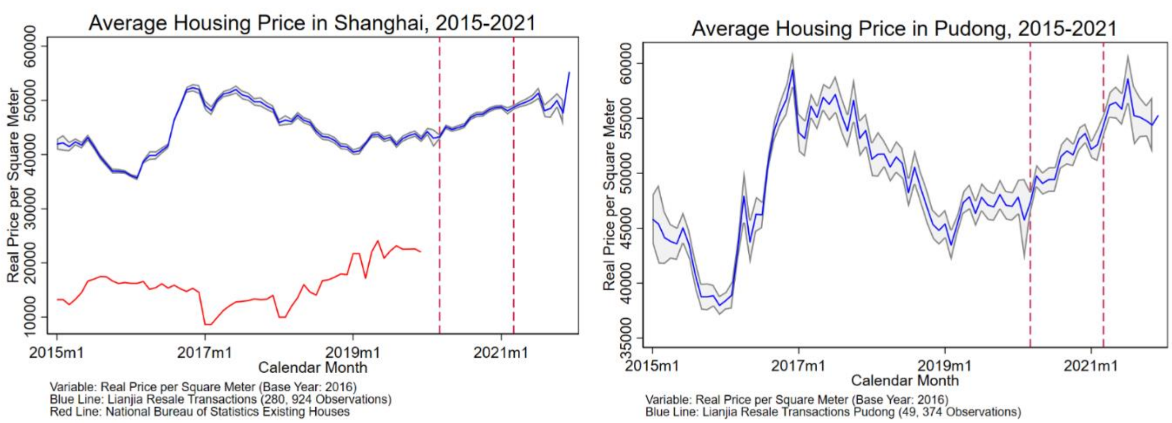

Figure 4 – 5. Average Housing Price in Shanghai; Average Housing Price in Pudong (Monthly)

There is no currently available public data on the total number of resale transactions per year or per calendar month in Shanghai. Thus, there is currently no way to judge whether the scraped transaction records accurately represent all resale transactions for the sample periods in Shanghai.

2. School District Data

Every March, SMEC-Pudong announces its middle school admission procedure as well as its assignment of nearly 17,000 residential addresses in Pudong to public middle schools. From the SMEC website and the SMEC-associated WeChat account (ID: Shanghai Fabu), this study scraped historical data on school district assignments in Pudong from 2015 to 2021. The residential addresses were keyed onto Gaode Map and their corresponding latitudes and longitudes were obtained. Finally, by forming a convex hull among the geographic coordinates belonging to each public school, the school district areas were defined.

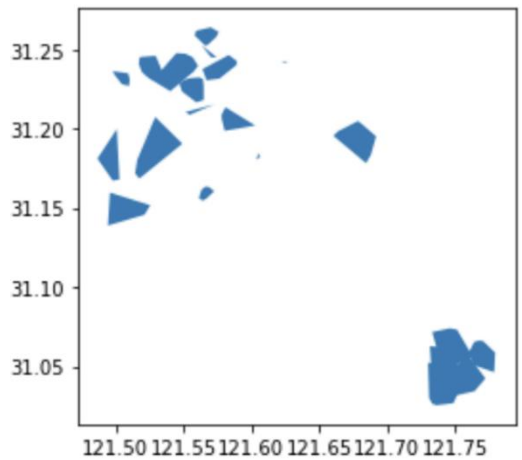

Figure 6. School Districts for Key Schools in 2021

From the 145 public middle schools in Pudong district, 15 quality public middle schools (or key schools) were identified based on rankings posted by commonly-used social networking sites such as Shanghai Xuekao, Zhihu, and Sohu. From similar platforms, the percentage of students sent to prestigious high schools per middle school in Shanghai was obtained and was also used as a reference. Figure 6 shows the 2021 school districts of the 15 identified schools. Note that not all school district sets are convex. This is because some households assigned to a public middle school can be far from other households assigned to that school.

3. Neighborhood Data

Compared to the Lianjia real estate website, Fang.com provides more detailed neighborhood information such as green space ratio and floor-to-area ratio. Hence, the most up-to-date neighborhood-level data points obtainable were collected from two sources, Fang.com and Gaode Map (for geographic coordinates). The coordinates of the 13,096 neighborhoods in our sample for Pudong were further inputted onto Gaode Map to obtain surrounding information such as the number of subways and bus stops in 500 meters [3].

Due to time constraints, local socio-demographic data were not obtained. According to Bayer et al. (2007), this lack of information will create bias in the observational results. Thus, in the future, the 2010 Chinese Census can be matched to the neighborhoods in the sample. However, given that neighborhood-level information can change due to mobility over time, data issues are still expected. At present, given the availability of data in China, a more viable method to account for demographic information is yet to be identified.

4. Descriptive Statistics

Each housing unit was spatially linked to its corresponding school district and school district boundary. In addition, each housing unit was matched to its neighborhood by constructing a weighted index from fuzzy matching of neighborhood names and residential addresses, and distances between geographic coordinates. Limiting the match ratio above a certain threshold resulted in a total of 48,392 data points from Pudong's sample.

Table 4 shows the descriptive statistics of the regression variables for the matched housing units and neighborhoods in Pudong. To determine the width around the school boundaries and ensure that regression discontinuity design works, mean comparison tests were conducted to check for significant differences in neighborhood characteristics on the two opposite sides of the boundaries. Despite limiting the width to about 250 meters near boundaries, which already results in significantly fewer data points, a significant

[3] Due to time constraints, a buffer size of 500 meters was used. In the future, different buffer sizes will be tested for use and distances to the nearest amenities will be measured.

difference in green space ratio between the two sides of the boundaries remains. This indicates the need to include a variable that can more comprehensively account for unobserved neighborhood characteristics. In the future, this study can reference the strategies used by Chan et al. (2020) and Han et al. (2021) where average rent per neighborhood is used as a holistic index of neighborhood quality. Meanwhile, all characteristics other than green space ratio show no significant differences even at a buffer of 1000 meters.

Figure 7 plots the conditional average of real housing prices and neighborhood characteristics in a given bin of distance from the school borders. Negative distance indicates households located outside of key middle school districts while positive distance indicates households located within key school districts. The housing price gap is around 10,000 yuan/square meter. Other characteristics exhibit small differences and continuous trends at the key school district boundaries.

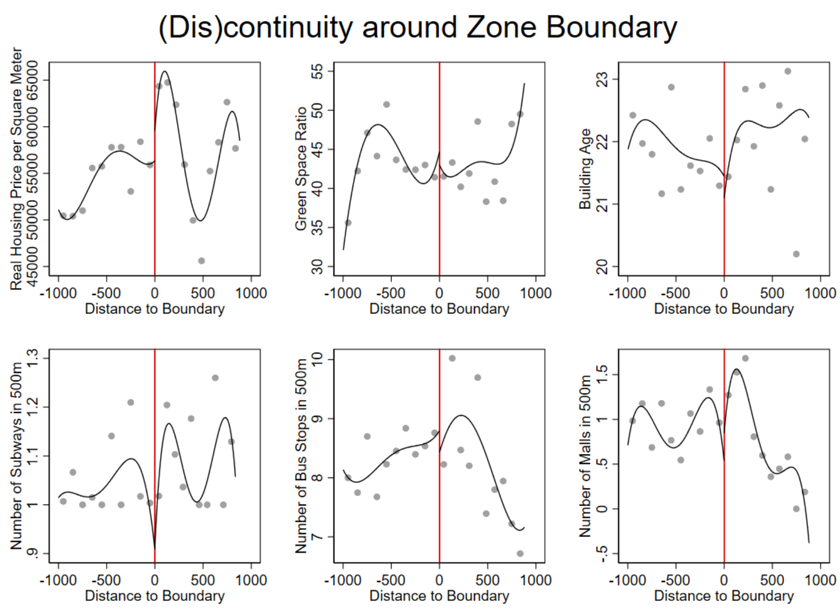

Figure 7. Housing Price and Neighborhood Characteristics Around Zone Boundary

Distance from Boundary	All Sales		Within 1000 meters		Within 500 meters		Within 250 meters	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Housing Unit Characteristics								
Real Price per Square Meter (Base Year: 2016)	48227.03	16113.12	55413.75	17112.95	56412.42	17760.96	57730.45	18229.87
Log(Price)	10.72518	0.367904	10.86954	0.356759	10.88387	0.372477	10.9082	0.361091
Area in Square Meter	143.3981	12745.3	211.6828	18864.5	261.9506	22448.94	80.14015	49.77485
Number of Beds	1.99907	0.82712	2.008801	0.869986	2.012271	0.857963	1.993205	0.844441
Face South?	0.901947	0.29739	0.891389	0.311157	0.897462	0.303364	0.895804	0.305534
Have Elevator?	0.383824	0.486321	0.344615	0.475253	0.315194	0.464608	0.2897	0.45365
Simple Decoration	0.199021	0.399268	0.223755	0.416769	0.220045	0.41429	0.21495	0.410812
Refined Decoration	0.278641	0.448335	0.289266	0.453432	0.288532	0.453094	0.293157	0.455237
Age of House	17.62099	9.295092	20.84561	9.28735	21.61927	8.93072	22.08202	8.58366
Neighborhood Characteristics								
Green Space Ratio	35.59314	11.39437	35.44943	13.49323	34.13761	13.10819	33.89404	12.5336
Floor-to-Area Ratio	1.918715	1.327684	2.012854	0.886242	2.021341	0.73077	2.007882	0.801351
Number of Subways in 500 m	0.363283	0.51802	0.457763	0.557691	0.48018	0.574849	0.618145	0.599065
Number of Bus Stops in 500 m	6.686167	2.655784	7.112512	2.730944	7.183938	2.836371	7.161779	2.83267
Number of Malls in 500 m	0.778761	1.092512	0.95522	1.321345	1.001992	1.486536	1.198522	1.685945
%Within Inner Ring	0.196251	0.397165	0.384539	0.486497	0.413171	0.492419	0.433596	0.4956
%Inner to Middle Ring	0.312965	0.463705	0.396697	0.489223	0.37912	0.485184	0.359919	0.480005
%Middle to Outer Ring	0.239068	0.426519	0.09804	0.297376	0.094635	0.29272	0.127086	0.33309
Observations	48392		22042		15565		8388	

Table 4. Descriptive Statistics of Variables Used

VI. Observational Results

Table 5 shows the hedonic price regression for housing units in the matched sample of Pudong from 2015 to 2021. Column 1 – 3 present the results of a simple hedonic price regression. Column 1 does not consider any characteristic, Column 2 considers housing characteristics, and Column 3 additionally considers neighborhood characteristics. Column 4 – 7 present the results from the boundary-fixed-effect method where Columns 5 – 7 restrict the sample within a distance band from the school border. Results indicate that the housing price premium significantly decreased from 19.8% to 12.3% when neighborhood characteristics were considered. This suggests that key public schools in Pudong are generally located within neighborhoods with better location qualities. Limiting the sample to households within a distance from school borders further reduced bias caused by the sorting effect and the average high-quality public middle school premium from 2015 to 2021 is estimated to be 6.43~8.39%.

Table 6 shows the results of the boundary-fixed-effect estimates within distance from boundaries for each period. Since SMEC announces admission procedure every March, each period begins from March of the current year and ends at the February of next year. For example, year 2015 in the table presents results for the period from March 2015 to February 2016. These estimates allow tracking of changes in housing price premiums over time. For example, using the 250-meter boundary as a reference, it can be noted that the education premium was highest in 2017, averaging up to nearly 13%. The next highest education premium was about 11% in 2015, following the full implementation of the nearby school policy. For years other than 2021, the premiums were generally between 6% and 8%. These observational results cannot answer the question regarding whether significant changes in housing price premiums for quality public middle schools were induced by the implementation of the 2020 middle school admission reform in March 2020. Although the premium decreased from roughly 7% 2019 to 6.8% in 2020, the difference was miniscule.

VARIABLES	(1) Log(Price)	(2) Log(Price)	(3) Log(Price)	(4) Log(Price)	(5) Log(Price)	(6) Log(Price)	(7) Log(Price)
Key School Indicator	0.223*	0.198*	0.123**	0.105**	0.0732**	0.0643**	0.0839***
	[0.119]	[0.104]	[0.0413]	[0.0375]	[0.0288]	[0.0251]	[0.0221]
Area in Square Meter		-4.10e-06***	-3.86e-06***	-3.84e-06***	-3.68e-06***	-3.68e-06***	0.000310
		[1.89e-07]	[1.99e-07]	[2.13e-07]	[3.51e-08]	[2.88e-08]	[0.000285]
Number of Beds		0.0177	-0.00552	-0.00272	-0.0141	-0.0252***	-0.0473***
		[0.0129]	[0.00989]	[0.00788]	[0.00843]	[0.00846]	[0.0110]
Face South?		-0.0141	0.0307***	0.0316***	0.0363***	0.0497***	0.0701***
		[0.00845]	[0.00396]	[0.00327]	[0.00378]	[0.0110]	[0.0179]
Have Elevator?		0.184***	0.0509***	0.0455***	0.0278	0.00558	-0.0392*
		[0.0260]	[0.0120]	[0.0125]	[0.0190]	[0.0204]	[0.0193]
Simple Decoration		0.0470***	0.00492	0.00992**	-0.0253*	-0.0241	-0.0187
		[0.0124]	[0.00738]	[0.00354]	[0.0131]	[0.0183]	[0.0184]
Refined Decoration		0.129***	0.0661***	0.0728***	0.0322*	0.0294	0.0236
		[0.00679]	[0.00510]	[0.00349]	[0.0165]	[0.0229]	[0.0223]
Age of House		0.00904***	-0.00373***	-0.00492***	-0.00800***	-0.00812***	-0.00584**
		[0.00130]	[0.000956]	[0.000777]	[0.000807]	[0.00116]	[0.00214]
Green Space Ratio			0.00410***	0.00380***	0.00282***	0.00346***	0.00125**
			[0.000572]	[0.000622]	[0.000619]	[0.000528]	[0.000518]
Floor-to-Area Ratio			-0.00827***	-0.00812***	-0.0233***	-0.0192**	-0.0310**
			[0.00259]	[0.00200]	[0.00478]	[0.00826]	[0.0109]
Number of Subways in 500 meters			0.0175*	0.00824	-0.00761	-0.0107	-0.00427
			[0.0101]	[0.0108]	[0.0148]	[0.0193]	[0.0341]
Number of Bus Stops in 500 meters			-0.00649***	-0.00439**	0.00421*	0.00507**	0.00887***
			[0.00202]	[0.00177]	[0.00204]	[0.00235]	[0.00216]
Number of Malls in 500 meters			0.0162***	0.0168***	0.0116	0.00227	-0.00212
			[0.00140]	[0.00467]	[0.00911]	[0.00764]	[0.0109]
Within Inner Ring			0.684***	0.578***	0.382***	0.364***	0.237***
			[0.0675]	[0.0383]	[0.0453]	[0.0642]	[0.0745]
Inner to Middle Ring			0.427***	0.363***	0.216***	0.170**	-0.0385
			[0.0193]	[0.00992]	[0.0462]	[0.0728]	[0.0734]
Middle to Outer Ring			0.252***	0.204***	0.201***	0.158*	0.0237
			[0.0174]	[0.00611]	[0.0587]	[0.0910]	[0.0858]
Observations	48,172	48,171	47,938	47,938	21,909	15,653	8,645
Adjusted R-squared	0.160	0.230	0.558	0.582	0.610	0.644	0.610
BDD Distance	All Sales	All Sales	All Sales	All Sales	1000m	500m	250m
Household Characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Boundary Fixed Effect	No	No	No	Yes	Yes	Yes	Yes
Cluster	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Regression Results for All Years

VARIABLES	(1) Log(Price)	(2) Log(Price)	(3) Log(Price)	(4) Log(Price)	(5) Log(Price)	(6) Log(Price)	(7) Log(Price)	(8) Log(Price)	(9) Log(Price)	(10) Log(Price)
Year		2015			2016			2017		2018
Key School Indicator	0.0891	0.0933***	0.111***	0.0805**	0.0827***	0.0682***	0.125***	0.116***	0.129***	0.117***
	[0.0581]	[0.0285]	[0.0250]	[0.0364]	[0.0281]	[0.0212]	[0.0362]	[0.0333]	[0.0276]	[0.0373]
Observations	3,145	2,196	1,233	2,848	2,079	1,127	2,346	1,752	1,001	2,557
Adjusted R-squared	0.321	0.630	0.630	0.615	0.665	0.714	0.428	0.422	0.399	0.508
BDD Distance	1000m	500m	250m	1000m	500m	250m	1000m	500m	250m	1000m
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Boundary Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ

(11) Log(Price)	(12) Log(Price)	(13) Log(Price)	(14) Log(Price)	(15) Log(Price)	(16) Log(Price)	(17) Log(Price)	(18) Log(Price)	(19) Log(Price)	(20) Log(Price)	(21) Log(Price)
2018			2019			2020			2021	
0.0796**	0.0735**	0.108**	0.0885**	0.0707**	0.0765*	0.0632*	0.0680**	0.0524	0.0361	0.0317
[0.0265]	[0.0285]	[0.0455]	[0.0337]	[0.0269]	[0.0423]	[0.0307]	[0.0312]	[0.0348]	[0.0286]	[0.0226]
1,857	1,067	2,981	2,126	1,190	6,267	4,424	2,425	1,719	1,146	568
0.656	0.556	0.629	0.698	0.657	0.496	0.738	0.643	0.645	0.790	0.729
500m	250m	1000m	500m	250m	1000m	500m	250m	1000m	500m	250m
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ	SAZ

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6. Regression Results by Year

However, following the announcement of the 2022 high school admission reform, it can be concluded that, at any boundary threshold, there are no significant differences between housing prices in non-quality middle school districts and housing prices in quality middle school districts. This result indicates that the said 2022 policy might have possibly dampened the effects of quality school districts on housing prices in Shanghai. That said, since the data points in this study are limited to December 2021, the sample size is smaller for the 2021 period compared to other periods. For a more representative result, a follow-up evaluation can be done when relevant data for the period before March 2022 are made available.

VII. Future Steps

This section discusses the future steps to advance the current study. As the research remains at an embryonic stage, the current proposal delineates as many ideas as possible, some of which bears a possibility to be eventually unfeasible.

1. Data Collection

One obvious change is to apply the current empirical strategy to the other administrative districts in Shanghai. There are two directions possible regarding this change. One is to only look at districts that abide by the nearby school policy; the other is to additionally look at how public primary school premiums have changed in response to the regional policy shocks in districts that assign students through their primary school status.

In addition, as illustrated in Sections III – V, the following describes the major parts wanting in the proposal:

(1) Local socio-demographic characteristics

(2) Controls for unobserved neighborhood traits

(3) Continuous measure for school quality

(4) Control group not yet affected by regional policy shocks

In the future, the 2010 Census data will be downloaded and matched to each neighborhood to obtain controls for demographic characteristics. In terms of unobserved neighborhood traits, this study intends to match each neighborhood with the neighborhood's average rent. Given that the nearby school policy only applies to homeowners rather than renters, average rent per neighborhood serves as a holistic control for all neighborhood traits other than access to education. Unfortunately, data sources revealing continuous measures of school quality have not yet been discovered.

Given that the two regional policy shocks produce effects on school districts with and without key schools, this study needs a control group, such as Hangzhou, where regional reforms have not been implemented. Afterwards, a triple difference estimator can be applied to estimate the effects post policies.

2. Identifying the Impact of the 2020 Admission Reform

From the observational results, it is unclear whether the 2020 admission reform has influenced the education premium. Household-level data is needed to differentiate the policy impact among households of different income-level and with different student performance. Unfortunately, such data do not exist publicly, and private data are necessary to accurately evaluate the 2020 policy impact. Alternatively, this study can broadly investigate the policy impact using neighborhood-level socio-demographic traits. Given that richer households have a higher probability of affording private schools and international schools, it is possible that compared to other households, they assign a lower utility to the value added to public school districts following the 2020 reform. Hence, this study can classify neighborhoods into different wealth categories and track the changes of the average willingness-to-pay of the different categories pre and post the policy implementation. In addition to the 2010 Census that does not account for changes in later years, Chan et al. (2020) discovered that quality private primary schools tend to locate in richer neighborhoods. Thus, it is possible to investigate whether the same phenomenon applies to middle schools. If so, for each housing unit, a "nearby private middle school quality index" can be constructed as follows:

$$index_{it} = \sum_k \frac{1}{d_{ik}} * \frac{1}{\sum_k \frac{1}{d_{ik}}} schoolquality_{kt} \ (5)$$

where d_{ik} is the distance between housing unit i and each private middle school k near i, and $schoolquality_{kt}$ presents some time-variant measure of school quality for k, depending on the availability of certain continuous quality measures. Each nearby private school is weighted by an inverse distance measure, which eventually amounts to a weighted geometric mean of school quality. This study can then differentiate tiers of housing units using the constructed index and examine how the aggregate willingness-to-pay of different groups responds to the 2020 policy. However, doing so does not help approximate student performance in households.

3. Triple Difference Estimator

Non-quality school districts cannot be compared with quality school districts in Shanghai to establish a counterfactual due to spillover effects among the two groups following the policy shocks. If another city with similar economic trends and education system to Shanghai has not yet implemented the aforementioned policies, it can be used as a control group to estimate the premium of quality school districts relative to non-quality school districts post policies.

Using our basic hedonic price regression model with BDD, the equation for triple difference is shown as follows:

$$ln(p_{i,n,t}) = \alpha_t + \beta_1 shanghai_i + \beta_2 key_{it} + \beta_3 post_t + \beta_4 shanghai_i * key_{it} + \beta_5 shanghai_i * post_t + \beta_6 key_{it} * post_t + \beta_7 key_{it} * post_t * shanghai_i + X_{it}\Upsilon + K_{nt}\delta + \theta_{bt} + e_{i,n,t} \ (6)$$

where $shanghai_i$ is a dummy of whether house i is in Shanghai, and $post_t$ is a time dummy for policy implementation. Other variables are the same as (4). The current study is interested in β_7, which, under standard OLS assumptions and the parallel trend assumption, will be the difference in willingness-to-pay between households in quality middle school districts in Shanghai after the policy as treated and had they not been treated. The triple difference estimator shows how the housing price premium has truly changed following the policies.

Before running the triple difference regression, the parallel trend assumption would need to be tested. In this model, the assumption is:

$$
\begin{aligned}
&(E[Y_0|shanghai = 1, key = 1, post = 1] - E[Y_0|shanghai = 1, key = 1, post = 0]) \\
&\quad - (E[Y_0|shanghai = 1, key = 0, post = 1] - E[Y_0|shanghai = 1, key = 0, post = 0]) \\
&\quad = (E[Y_0|shanghai = 0, key = 1, post = 1] - E[Y_0|shanghai = 0, key = 1, post = 0]) \\
&\quad - (E[Y_0|shanghai = 0, key = 0, post = 1] - E[Y_0|shanghai = 0, key = 0, post = 0]) \quad (7)
\end{aligned}
$$

4. Robustness Check

4.1 Rental Data

	Mean	SD
Rent	4710.354	4675.647
Area	78.00514	45.5282
Building Age	14.94475	8.554313
% Houses Facing South	0.950784	0.216338
Observations	5547	

Table 7. Rental Data Summary Statistics

As mentioned in Section III, renters do not share the benefits from nearby school policy, so rents reflect neighborhood characteristics other than access to education. Hence, changing the dependent variable from resale transaction price to rent shows whether there exist any significant differences between neighborhoods in key school districts and non-key school districts caused by the sorting effect. To prepare for the robustness check, 5,547 rental data in Pudong from Lianjia from January 2015 to December 2020 has been collected. However, due to time constraint and the computationally extensive web-scraping procedure, this study has not yet completed data collection and the geospatial processing procedure. Table 7 shows the descriptive statistics of the rental data available so far.

4.2 Matching Strategy

Another potentially viable robustness check is a matching strategy conducted by Fack & Grenet (2020), which accounts for unobserved neighborhood characteristics if such characteristics change along a boundary. Specifically, the matching strategy obtains the residuals of house *i* assigned to boundary *b* and school s at time t – $p_{i,b,s,t}^{residual}$ – from the hedonic price regression where housing characteristics and neighborhood characteristics are controlled for. The matching strategy then constructs a control price for house *i* as follows:

$$p_{control,i,b,s',t}^{residual} = \sum_j \frac{1}{d_{ij}} * \frac{1}{\sum_j \frac{1}{d_{ij}}} p_{j,b,s',t}^{residual} \quad (8)$$

where s' is the assigned school at the opposite side of *i*'s school attendance zone. $p_{j,b,s',t}^{residual}$ is the time-variant residual price of every house *j* within the boundary width and within the attendance zone of s'. These opposite residual prices are weighted by an inverse distance measure, where d_{ij} is the distance between *i* and *j*. The control price explains what the price would have been if house *i* had been placed in the attendance zone of s' instead of s, ceteris paribus. Then, results from a differential regression model (taking the difference between *i*'s residual housing price and the control price) give the willingness-to-pay if school assignment changes from s to s'. Aside from this strategy, there are also other similar spatial matching strategies such as those used by Gibbons & Machin (2003; 2006).

VIII. Conclusion

This research proposal attempts to understand the housing price premium in Shanghai, China, following the three education policy implementations. The aim of this research is to provide an accurate estimate of the changes in housing price premium due to the policy shocks. Due to the computationally intensive nature of this research, only observational results were offered using a hedonic price regression with a boundary discontinuity design. Although effects following the 2020 admission reform cannot be observed, there are promising results associated with the announcement of the 2022 admission reform. Results signal that the high school admission reform might have been effectively fulfilling the “common prosperity” goal set by the Chinese national government. To further identify causal effect, this study intends to employ a triple difference estimator. To justify the performance of the model used, robustness checks through the use of rental data and through the use of a cross-boundary differential model will be applied.

Although unable to identify the effect post 2020, the significant change of housing price premium pre and post the 2022 policy announcement indicates that, many parents value quality public middle schools due to their good placements to magnet high schools, although correlation between quality middle school enrollment and quality high school admissions does not imply causation. Hence, weakening the link between high school placement and middle school placement might serve as an effective strategy to dampen the education premium of quality middle schools.

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