China Economic Review 69 (2021) 101683

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

How does school district adjustment affect housing prices: An empirical investigation from Hangzhou, China

Ying Peng [a], Chuanhao Tian [b,c,1], Haizhen Wen [c,d,*]

[a] School of Urban Planning and Design, Peking University, Shenzhen 518055, China
[b] School of Public Administration, Zhejiang University, Hangzhou 310058, China
[c] Center for Real Estate Studying, Zhejiang University, Hangzhou 310058, China
[d] Department of Civil Engineering, Zhejiang University, Hangzhou 310058, China

ARTICLE INFO

Keywords:
Capitalization
Property price
Omitted variables
Difference-in-differences
Heterogeneity
Quantile regression

ABSTRACT

A quality promotion of neighborhood primary schools no doubt elevates nearby housing price. But which houses benefit from the public policy is important to improve educational equity. Accurate identification of such capitalization effects will help policymakers optimize the allocation of scarce public goods. Previous studies on this issue have been biased due to endogeneity and overlooking the impacts of facility quality change. Based on the Hangzhou's school district adjustment in 2012, the current work contributes to housing price effects of policies and education quality changes, rather than a static educational facility. The difference-in-differences model with quantile regression is constructed to obtain a more precise and detailed estimation among the different sub-markets. Results show that the average price effect estimated by the difference-in-differences is up to nearly 800 yuan/m^2, higher than cross-sectional estimation. Only housing with better schools after reassignment witness a price premium. Low-priced and small houses earn more than 1000 yuan/m^2, whereas high-priced and large houses are not significantly affected. The results demonstrate that future policies should ensure the rights of low-income groups to attend high quality primary school and guard against the gentrification of low-priced houses.

1. Introduction

When public educational facilities are extremely scarce, housing often becomes the major intermediary mechanism for residents to obtain access to an educational facility. Residents are required to attend public primary schools near their houses in accordance with the Nearby Enrollment policy. As a result, houses that have access to institutions offering high-quality education are in greater demand and therefore cost more. The huge price premium brought about by better educational resources means that the local financial investment in public education is *capitalized* into property prices or purchasing costs. This is also known as the *capitalization effects* of schooling (Oates, 1969). The capitalization effects of educational resources reflect the allocation of public goods and represent local residents' purchasing costs for public goods.

The capitalization effects referred to here can be examined from different perspectives, including the quantity (Feng & Lu, 2013)

* Corresponding author at: Center for Real Estate Studying, Zhejiang University, Hangzhou 310058, China.
E-mail addresses: pengying@pku.edu.cn (Y. Peng), tch@zju.edu.cn (C. Tian), ningduwhz@hotmail.com (H. Wen).
[1] Co-first author

https://doi.org/10.1016/j.chieco.2021.101683
Received 3 December 2020; Received in revised form 2 August 2021; Accepted 16 August 2021
Available online 18 August 2021

and quality of neighborhood education resources (Wen, Gui, Tian, Xiao, & Fang, 2018). Because people are more concerned with the quality of the specific school they will attend than the number of schools available to attend, the quality of educational resources has far-reaching significance on the development of humans and society. Hence, increased attention and relevant research on the quality of educational facilities are needed.

Notably, investigations of such capitalization effects in previous studies have been subject to endogeneity and estimation bias, caused by omitted variables and self-selection during the project placement and residential location (Nguyen-Hoang & Yinger, 2011; Livy & Mitchell Livy Mitchell, 2017). Some studies have improved these problems by using boundary fixed effects (Beracha & Hardin, 2018; Dhar & Ross, 2012), instrumental variables (Bae & Chung, 2013; David, 2011; Rosenthal, 2003), and difference-in-differences (DID) (Feng & Lu, 2013; Ries & Somerville, 2010). But the application of methodology and characterization of heterogeneity among the submarkets can still be improved. The validity of DID needs further explanation and verification, and the variation of the capitalization effects under different situations needs to be further depicted.

Therefore, this study viewed the school district adjustment (SDA) of public primary schools in Hangzhou, China in 2012 as a case to explore the capitalization effects of educational resources. It contributes to previous research by (1) emphasizing the changes in education quality brought about by policies and measuring the price effects of education quality within a policy context, (2) considering the issues of endogeneity and using effective tools to accurately identify the capitalization effects, and (3) depicting the variation of capitalization effects within different submarkets, to get a detailed policy evaluation and well-directed policy implication to tackle educational dilemmas.

This paper is structured as follows: In the first part, we introduce the purpose of this work. In the second part, we review previous studies and present the research problems. In the third part, we introduce the institutional background data, and methods. In the fourth part, we show the results of the empirical analysis. In the fifth part, we present the corresponding discussion, and in the last part, we summarize the arguments of this study and suggest relevant policies.

2. Literature review

To investigate the price effects of educational public goods, scholars have studied various features of educational resources, including the availability of supporting facilities, the number of educational facilities, the distance between educational facilities and houses, as well as the quality of educational resources. For example, Bogart and Cromwell (2000) concluded that the cancellation of the qualification to attend a neighborhood school reduced housing prices by 9.9%. Feng and Lu (2013) used the case of Shanghai to illustrate that an increase in the quantity of the best-quality high schools per square kilometer would result in a 21.7% increase in the average price of a property in the relevant region. Wen, Zhang, and Zhang (2014) studied the educational facilities in Hangzhou and found that the shortest walking distance to a junior high school has a significantly negative effect on housing prices, whereas the distance to the primary school has no effect. In addition, Zheng, Hu, and Wang (2015) calculated that a within-zone housing unit sells at 2266 yuan/m^2 more than housing units outside the attendance zone of a key primary school.

Although all of these studies examined the price effects of educational resources, a theoretically different mechanism exists when different factors are studied. First, in China, preschool education and high school education is not part of compulsory education, namely public service. It means that students receive preschool education and high school education through an explicit market, rather than an implicit market in the Tiebout (1956). Second, the price effects of the distance between housing and the school illustrate a trade-off of commuting costs and purchasing costs, as well as safety and additional time for recreational facilities (Huang and Hess, 2018; Jun, 2018), rather than the allocation of public goods. Moreover, practically, residents focus on the school they will attend. Except for that particular school, other schools would not have excessive influence on the results of their educational achievement. So, to echo the literature on capitalization effects of schooling, we should also focus on the effect of education quality on property prices.

Oates (1969) first used expenditure per student to measure education quality with cross-sectional data from 53 communities in New Jersey in the United States and found that a $100 increase in expenditure per student appreciates the housing price by $1200. Black (1999) used test scores to measure education quality and found that parents' willingness to pay for housing will increase by 2.1% if test scores increase by 5%. Rosenthal (2003) used similar indicators to show that the elasticity between housing prices and General Certificate of Secondary Education test scores is 0.05. In addition, teacher–student ratios and enrollment rates into key high schools were used as independent variables to measure the impact brought about by the quality of educational resources on property prices by Bae and Chung (2013). In Korea, Bae and Chung (2013) illustrated that the proportion of public secondary school students who are admitted to Seoul National University has a significant positive effect on housing prices and parents' choice tendency. Many other indicators have been used to evaluate education quality in China. For instance, Wen, Xiao, Hui, and Zhang (2018) used questionnaires to investigate residents' evaluation of public primary schools and score the education quality. Their results show that education quality and housing prices have approximately 6% elasticity (Wen, Xiao, & Hui, 2019). The quality of education can also be expressed by whether an institution is a key or normal school recognized by the state. Mao, Luo, and Pan (2014) estimated that the housing premium for properties near key primary schools in Hangzhou is 12.8%, which is lower than near key secondary schools. Feng and Lu (2013) found the capitalization effects of normal high schools (best-quality schools) in Shanghai were higher than that of key secondary schools.

These studies have reached the following consensus: an increase in the quality of educational facilities will have a significant positive impact on nearby housing prices. However, these studies are mainly based on cross-sectional or pooled data, and they ignore the endogeneity problem. Other attributes, especially unobserved ones, are not fully modeled to capture the impact of educational resources. Therefore, they would improperly contribute a price premium independent of the schools to educational resources, which results in a serious estimation bias.

Three circumstances lead to endogeneity in the above research. First, these studies omit some important factors and cause the error term in the regression to be correlated to the independent variables, thereby dissatisfying the hypothesis of unbiased estimation. Wen, Lu, and Fu (2005) comprehensively analyzed three types of characteristics affecting housing prices. Cemeteries and landscapes (e.g., residential buildings built near golf courses or lakes) as neighborhood features will significantly impact housing prices, but these factors have not been considered in many studies. When residential sorting is considered, more factors have been overlooked, including household income, local amenities, and student quality. Such factors cannot be directly observed in essence, but they are closely related to the dependent variables concerned (Bayer, Ferreira, & McMillan, 2007). Bayer, Mcmillan, and Rueben (2004) used the example of San Francisco to show the impact of educational resources and average income of the community decreases when the regional fixed effect is controlled, whereas the characteristics of ethnic composition lose their significant impact. Thus, ignoring the unobserved factors of the region or residential area will lead to the overestimation of the *implied price* of features. Second, the temporal trend of a macroeconomy can be a source of an unobserved factor in the current study. During a boom, property prices would increase. Comparison only between different periods might improperly contribute appreciation from a boom to a promotion of education quality. Third, self-selection problems will also lead to estimation bias. In China, schools are financed by local governments, and public projects usually are constructed at certain places based on the governments' goals. Therefore, project placement can be influenced by the current housing market and living pattern for different original objectives. For instance, the local government might construct a subway station where the land price is cheap to decrease the expropriation costs and increase the land-leasing revenue in the future (Yang, Chen, & Le, 2016), or they might build better school in densely populated areas with high housing prices to affect more people (Zheng et al., 2015).

To address endogeneity issues, some scholars have proposed different solutions to obtain an accurate estimation of the capitalization effect. Black (1999), Dhar and Ross (2012), Gibbons et al., (2013), and Beracha and Hardin (2018) used boundary fixed effects to measure the capitalization effects of students' test scores on housing prices. Black (1999) also showed that the estimates of capitalization effects based on boundary fixed effects are only half of those in ordinary linear regression. To eliminate the impact of unobserved factors around school district boundaries caused by household sorting (Bayer et al., 2007; Livy Mitchell, 2017), Zheng et al. (2015) paired the houses on two sides of school district boundaries in accordance with the observable characteristics. Then, they excluded the impact of unobserved factors from estimating through the institutional basis of "renting and buying with different rights." In addition to boundary fixed effects, David (2011), Rosenthal (2003), and Bae and Chung (2013) used geographical features as instrumental variables to examine the impact of education quality on housing prices. Furthermore, other studies used DID based on quasi-experiments to estimate the effects of policies leading to changes in educational resources and reflect the price effects of education quality. For example, Wen, Xiao, and Zhang (2017) selected the Zero-Choice School policy in Hangzhou, China as the quasi-experimental background. Their findings indicate that a one-unit improvement in the quality of a designated primary school will result in approximately a 1.5% rise in housing prices. Ries and Somerville (2010) used the case of Vancouver SDA in Canada to illustrate that a one-standard-deviation improvement of junior middle school teaching quality will cause housing prices to significantly increase by 1%–2%. Similar research ideas influenced Bogart and Cromwell (2000) analysis of banning three schools in Shaker Heights in the United States, Zahirovic-Herbert and Turnbull's (2008) analysis of public school enrollment adjustment in East Baton Rouge Parish in the United States, and Feng and Lu's (2013) analysis on Shanghai Municipal Education Commission's nominating an experimental representative high school in China.

The shortcomings of DID-based analysis mainly include three aspects. First, these studies only focus on the housing price changes caused by educational policies, but they ignore the impact of the changes in education quality caused by the education policy. For example, Bogart & Cromwell, 2000found that the SDA causes housing prices to decline for those who lose initial designated educational facilities. However, Bogart did not investigate the changes in new supporting educational resources brought about by the policy and ignored the impact of the changes in the corresponding educational quality. Feng and Lu (2013) explored the impacts of the number of high schools in the region after the Shanghai Municipal Education Commission named the experimental representative high schools, ignoring the impact of educational resource quality. We need to focus on education quality because the quality of schools and their relevant changes often have a greater effect than the policy changes or number of schools on the residents' choice when educational resources are extremely scarce, especially with China's nearby enrollment and zero-choice policies. Therefore, the significance of identifying education quality lies in accurately depicting residents' preferences for education as public goods. Such an accurate depiction will optimize the allocation of resources and enhance the equity of education. As such, high-quality education resources will not become too expensive to bear for most groups. At the same time, investigating the impacts of education quality on housing prices helps in understanding the causes of property price fluctuations, and identifying preferences toward educational resources can help policymakers anticipate future changes in housing prices caused by forthcoming policies.

Second, these studies do not elaborate on the premise of quasi-experimental analysis or test the parallel paths before using the DID model. Ashenfelter and Card (1984) emphasized the possible sample selection issue and potential solution by examining parallel paths. Under the parallel paths assumption, in the absence of treatment, the average outcome change from any pretreatment period to any posttreatment period for the treated is equal to the equivalent average outcome change for the controls. Hence, the counterfactual level of the treatment group can be estimated by calculating the changes in the control group (Mora & Reggio, 2015). Then, the problem of omitted variables will be solved and an unbiased identification will be obtained. This concern is important in isolating an accurate parameter of the treatment (Besley & Case, 2000). However, this important assumption has not been given enough attention or explained in previous papers on the capitalization effects of educational resources.

Finally, these studies do not properly describe the heterogeneity of the capitalization effects of education quality (Collins & Kaplan, 2017). First, public goods, such as education, need to be allocated in the housing market, as residents often decide the residential location in accordance with their income, supply, and policy constraints. The relationship between schooling and housing prices can

vary (Cheshire & Sheppard, 2004) and, therefore, the pattern of capitalization effects can help explain the different public good allocation mechanisms among various groups, regions, and times (Kirstine, 2014; Pilgram & West, 2018; Turnbull, Zahirovic-Herbert, & Zheng, 2018). Second, the purpose of public good allocations is to effectively meet the varying needs of residents through policy implementation. The depiction of the heterogeneous capitalization effects helps explain the heterogeneity of demand because housing price is a direct manifestation of consumers' preferences, thereby providing differential supply. The model of studying heterogeneity is widely used to examine housing prices (Wen et al., 2017; Wen et al., 2019), but it is often neglected when DID is applied to achieve an accurate estimation. Third, many believe that the housing market is not a homogeneous entity in which different submarkets exist. Identifying the variation between submarkets can help improve the predictive ability of the model and the accuracy of policies (Goodman & Thibodeau, 2010). Therefore, the heterogeneity of capitalization effects must be studied further in the present investigation.

Since the treatment group in an SDA is usually small, the division of samples would lead to incomplete information and selection bias (Newsome & Zietz, 1992). Although ordinary least squares is a widely used method for obtaining separate estimations, it would truncate the dependent variable and make each subsample sensitive to outliers. This could happen especially when houses in a treatment group of similar prices might be concentrated (Ries & Somerville, 2010). On the contrary, no division of sample is needed and there is no selection bias in quantile regression. Methods combing DID and quantile regression can be used to improve the accuracy of effect estimation (Callaway, Li, & Oka, 2018).

Based on the literature presented above, this work aimed to accurately investigate the capitalization effects of education quality rather than the quantity (Feng & Lu, 2013). It viewed Hangzhou's 2012 SDA as the quasi-experimental treatment and further verified the validity for the application of DID ignored in previous studies (Ries & Somerville, 2010). Each house was taken as the research object and the price premium was estimated within a DID framework to solve endogeneity problems. Last, the variation of effects among submarkets was depicted by a quantile regression as an addition to existing work (Wen et al., 2017).

3. Methodology

In accordance with previous studies, this work utilized the microdata of second-hand housing transactions in Hangzhou from June 2011 to May 2013. We viewed the SDA of public primary schools as the quasi-experimental background and used DID to eliminate the influence of unobserved factors to improve its estimation of education quality's impact on housing prices. Quantile regression and divided regression were applied to compare the impacts of different housing prices and obtain a robust and comprehensive estimation. In this section, we first introduce the institutional background of primary education and later illustrate the measurement of the corresponding educational facility quality. Then, we briefly introduce the second-hand housing transaction record as well as DID and quantile regression models for analysis.

3.1. Institutional background

3.1.1. Household registration and enrollment in public primary school

The household registration refers to the investigation, classification, and administration of the household within the jurisdiction of the local government. Although the current system in China is no longer as restrictive as it was before 1984 (Chan, 2009; Chan, Liu, & Yang, 1999), household accounts in different cities stand for different levels of local social welfare. Even in the same city, residents with different kinds of household registration will have different levels of social welfare, including public education.

In Hangzhou, according to the principle of nearby enrollment, school-age students go to the neighborhood public primary school designated to the house in which they live. This is also what we often call *zoning (assigning catchment area) enrollment*. Theoretically speaking, students living in the catchment area without owning a property (e.g., renting) still have the opportunity to study in the high-quality primary schools, which are more popular among local parents. Nevertheless, the quantity of such schools is very limited. The number of school-age students meeting the principle of nearest enrollment usually exceeds the capacity of these high-quality public primary schools. Therefore, students with a household account and housing in that school district will have the priority to enroll in that high-quality school. Houses with high-quality school districts are often sought after by parents because of the proximity of educational resources and the advantage of obtaining admission opportunities. Hence, the access to a public primary school and the purchase of property are closely linked, as the real estate location determines the public primary school for school-age students. Accordingly, the housing market has become the main allocation mechanism of educational resources.

3.1.2. SDA in 2012 in Hangzhou

The demand for high-quality primary education keeps increasing, which means the supply and demand of some public primary schools might be unbalanced. Therefore, the District Education Bureau announces and changes the catchment area of primary schools after April and before June based on the demographic census in March. Four of the six local bureaus announce the school catchment area by listing the assigned communities and the other two announce in form of describing the geographical boundaries of the school district. This means that the properties of some communities may be redistricted from the service area of school A to that of school B. Correspondingly, the education received by school-age students will also change from school A to B, and the quality of educational resources will change accordingly. Hangzhou's 2012 SDA involved 17 of 556 communities, 7 of 143 school districts and a small proportion of the sold properties (less than 5%). Residents have a stable expectation of supporting the primary schools in the community until the official announcement. This means that residents cannot influence or predict adjustment through pretreatment activities (such as protesting) and that the time of SDA is clearly identified. No anticipatory effects exist which would interfere with the

identification of incident impacts. These points illustrate that an SDA could be the perfect background for quasi-experimental analysis, which reduces several internal validity threats without complicated approaches (Meyer & Breed, 1995). Therefore, this paper used the SDA in Hangzhou in 2012 as the research object to investigate the relationship between education quality and housing prices.

Several similar SDAs exist around the world. This section introduces examples to illustrate the contribution of using Hangzhou's SDA as the setting to research school quality. One example is provided by Bogart and Cromwell (2000) in Shaker Heights in the United States. The purpose of the SDA in Shaker Heights was to change the composition of the local school. Three neighborhood schools were closed and the catchment areas of the remaining six schools were reassigned, five of which have undergone tremendous changes. This SDA altered the proportion of non-White pupils in primary schools to a great extent. The change of the zoning was so substantial that the school quality was changed by the new composition in an immeasurable way, even though the expenditure and the grade remained the same. Therefore, the SDA in Shaker Heights should not be used to analyze the impact of quality of educational resources because, according to the authors, so many variables were omitted that cannot be captured. Bogart and Cromwell (2000) research only examined the impact of closing neighborhood schools. Additionally, the mechanism was not the allocation of educational resources through the housing market but rather the changes in peer effects and accessibility.

Another example is the SDA in Vancouver, Canada (Ries & Somerville, 2010), which has greater similarity to the situation in Hangzhou: only a portion of houses were redistricted from one catchment area to another and the time is clearly identified. Although both SDA policies are perfect settings for quasi-experimental analysis, the imbalance between supply and demand of educational resources is greater in Hangzhou and this situation leads to a priority for homeowners over renters to enroll in the neighborhood public school. According to the World Bank,[2] the teacher–student ratio in Canada is 17, whereas it is 22 in China. In Vancouver, students from tenant households have the same opportunities as those from owner households to enroll in the public school. However, in Hangzhou, renters have the same chance just theoretically. The undersupply of public schools forces local governments to associate housing ownership with the priority of enrollment in practice, which strengthens the capitalization effects of SDA in Hangzhou. Therefore, our analysis of Hangzhou can serve to demonstrate the strong capitalization effects in developing countries that consistently face a resource shortage.

3.1.3. Other providers of primary education: private schools

In Hangzhou, besides public primary schools, there are also more than 30 private primary schools. Enrollment in a private primary school usually does not require a household account in Hangzhou or ownership of property. However, it does require school-age students to participate in the examination and selection. The admit scale is as low as 5%, and enrollment of private school and public school are independent of each other. This means that during the decision-making for a housing purchase, residents will not give up striving for the public schools regardless of the existence of private primary schools because no resident can guarantee that their children will be admitted to a private school. Some parents will choose to live in catchment areas with lower housing costs in the hopes of being admitted to a private school and not attending the neighborhood public school in an effort to lower their living expenses. In conclusion, as long as private and public enrollment requirements are independent of each other, residents will consider the quality of public primary schools and housing prices together to serve different purposes depending on the goal of the family (e.g., to secure high-quality education or to reduce housing costs).

3.2. Measurement of education quality

The quality of neighborhood educational facilities (Edu) is the variable of interest in this study. The measurement adopted in this study is based on a questionnaire survey with 660 residents in residential communities. The quality of the primary school is divided into four levels: if the primary school is a key school, school quality is scored 3, among them, the top 10 primary schools are scored 4; if around the average level, school quality is scored 2; and if below average, school quality is scored 1. A total of 20 residents were randomly selected in each residential community and required to grade the education quality in the urban area. The final score of each public primary school was calculated in accordance with the results of the questionnaire.

3.3. Transaction records of second-hand residential housing

We used each set of second-hand houses as the basis of the empirical analysis. In comparison with the average price of residential communities or regions (Feng & Lu, 2013; Wen, Xiao, et al., 2018), detailed transaction data allows us to include a greater number of factors, such as the building features of houses. Hence, we sorted out all second-hand housing transaction data from June 2011 to May 2013, which were provided by a real estate agency. The distribution of observation included in the database is shown in Fig. 1Figure 1 This database covers transaction-related information, including transaction price (**HP**), transaction time, building area, and floor (**Floor**) where the house is located. In addition, we used a similar questionnaire in part 3.2 to collect environmental and location features of the communities in which these second-hand houses are located, including the quality of the external environment (**Q_nature**), the quality of the internal environment (**Q_community**), and transportation accessibility (**Q_transport**). We then employed electronic maps (Fig. 1) to calculate other location features of the communities, such as the distance to CBD (**D_CBD**). The definitions of variables mentioned are shown in Table 1 and descriptive statistics are shown in Table 2. (See Figs. 1 and 2

[2] https://data.worldbank.org.cn/indicator/SE.PRM.ENRL.TC.ZS?view=chart

3.4. Hedonic pricing and regression models

Our empirical analysis focused on the hedonic pricing model, which has been widely used in previous studies (; Jun, 2018; Lancaster, 1966; Rosen, 1974; Zhang and Dong, 2018). This model emphasizes that consumers buy a *combination of features* of residential buildings, and each feature has its own *hidden price*, which can be implied via econometric methods. We chose to combine the idea of DID and quantile regression to improve this model (Emran, Robano, & Smith, 2009). Apart from DID, Regression Discontinuity Design could also be a useful tool to analyze the price effects of SDA. But the catchment announcement in form of listing assigned communities limits the description of the clear geographical boundaries. And we are not able to find adjacent houses located in different school districts to realize the Regression Discontinuity Design. Therefore, we investigate the impact based on a single DID.

First, we assigned the transaction price of each second-hand house as the dependent variable to perform the regression of the hedonic pricing model. The independent variables include **Edu**, whereas the control variables include architectural, location, and neighborhood features (Wen et al., 2005). The equation is as follows:

$$HP = \alpha_0 + \alpha_1 Edu_j + \beta S_i + \gamma L_j + \delta N_j + \eta_i + \varepsilon_i \quad (1)$$

where **HP** represents the transaction price of each set of second-hand houses; **Edu** represents the education quality of the public primary school designated to the second-hand house; coefficient α_1 measures the capitalization effects; S_i is the structural features of the second-hand house **i**, including **Floor** (Christopher, 2019), **Age (**Mulligan, Franklin, & Esparza, 2002**)**; L_j is the location features of the community **j** in which the second-hand house **i** is located, including the distance to CBD (**D_CBD**) (Alonso, 1964) and the transportation accessibility (**Q_transport**) (Pilgram & West, 2018); and N_j is the neighborhood features of the second-hand house, including **Q_nature**, **Q_community**, and **Q_sports (**Wen et al., 2017). η is a term for unobserved features and ε_i is the error term. α_1 is the key coefficient to be estimated.

To control for unobserved factors at community levels and during different time periods, community level fixed effects λ_j and time-fixed effects at the month level μ_t were added to the equation. When community fixed effects are added to the model, the time-constant community level variables should be deleted to avoid perfect collinearity. And Model (1) is further constructed into Eq. (2):

$$HP = \alpha_0 + \alpha_1 Edu_j + \beta S_i + \lambda_j + \mu_t + \eta_i + \varepsilon_i \quad (2)$$

Among them, S_i is individually-specific control variables. λ_j and η_i is time-constant. And μ_t is time-varying. Cluster-robust variance at the neighborhood level is controlled in all of the regressions based on Colin Cameron and Miller's work (Colin Cameron & Miller, 2015).

As discussed in the literature review, the omitted unobserved variables η correlated with education quality can result in the estimation bias of α_1. Hence, we adopted DID to deal with this problem. Specifically, we took the second-hand house in the community facing SDA as the treatment group and the second-hand house whose school district remains unchanged as the control group. To guarantee comparability in a practical sense, only the observations which are located in the same school catchment area as those in the treatment group, are selected as the control group in the analysis. By comparing the housing price difference before and after the adjustment, we eliminated the influence of the unobserved individual features. In addition, by comparing the changes between the treatment and control groups, we further eliminated the impact of unobserved macroeconomic features.

One key premise of the unbiased estimation is to show that the trend of the treatment group can be measured using the trend of the control group in the absence of policy shocks. The parallel paths of the control and treatment groups before the quasi-experiment can demonstrate comparability (Besley & Case, 2000; Meyer & Breed, 1995). The trend of the average housing price in the treatment and control groups is illustrated in Fig. 2Figure 2. As the SDA time in each urban district is different, only the second-hand housing prices in the non-experimental period (i.e., the second-hand housing prices before the adjustment in each urban district) are shown in Fig. 2. As shown in the figure, there is no obvious price gap between the treatment group and the control group prior to SDA. But the price difference is clear after SDA. Further examination of the parallel paths using the econometric model is presented in Table 3. We kept the observations before SDA and shift the time of treatment to an earlier date by 1–5 months. Then we applied the DID model to estimate the impact of assumed SDA. The result in Table 3 shows that the parallel path is satisfied. Additionally, we compared the baseline characteristic of the treatment group and the control group in Table 4. There is some initial difference upon community

Table 1
Measurements and definition of the variables.

Variable classification	Variable	Variable definition and measurement	Model approaches
Variables of interest	HP	Housing price (RMB/ square metre)	Provided by a real estate agency
	Edu	Quality of neighborhood public primary school, rating on a four-point scale	Graded by a questionnaire
Structure	Floor	The floor where a house is located.	Provided by a real estate agency
	Age	The age of a house.	Provided by a real estate agency
Location	D_CBD	The shortest walking distance between a community and CBD.	Calculated by ArcGIS
Neighborhood	Q_transport	Traffic conditions around the community, rating on a five-point scale	Graded by a questionnaire
	Q_nature	External environment conditions around the community, rating on a five-point scale	Graded by a questionnaire
	Q_community	Internal environment conditions around the community, rating on a ten-point scale	Graded by a questionnaire
	Q_sports	The overall quality of sport facilities in a community, rating on a five-point scale.	Graded by a questionnaire

Table 2
Description of variables mentioned.

Variables	Obs.	Mean	St. Error.	Min	Max
HP	1307	18,634.19	4906.13	8195.48	62,176.17
Edu	1307	2.01	0.74	1	4
Floor	1307	10.59	8.45	1	38
Age	1307	7.16	4.21	1	28
D_CBD	1307	8.59	2.38	2.46	12.79
Q_transport	1307	2.72	0.82	1	5
Q_nature	1307	3.24	0.70	1	5
Q_community	1307	3.79	0.65	1	5
Q_sports	1307	3.28	1.28	0	5

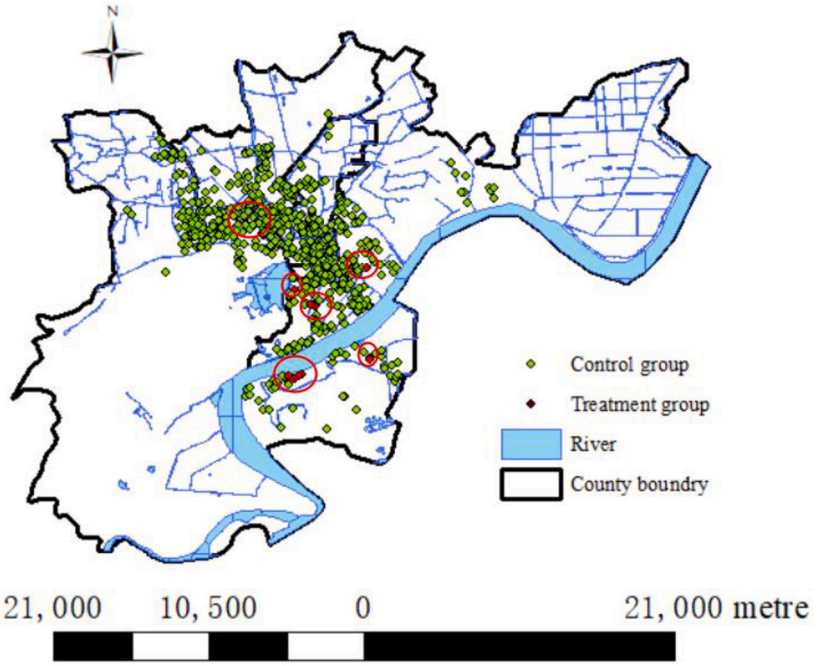

Fig. 1. Distribution of residential communities in central districts.

features and house ages.

This difference might come from that houses in good condition is easy to sell out under changing economic environment, which does not change the future appreciation rate. Houses with good location meet people's residential preference (Wu, Zhang, & Dong, 2013) and might have high appreciation rate in the long run but the distance to CBD is similar between groups. The estimation is not biased as long as those baseline features do not affect the slope of the time trend (Kahn-Lang & Lang, 2020). The above tests illustrate that in the absence of the SDA, the housing price of the treatment group will develop in the same trend as that of the control group. This counterfactual hypothesis means that the price change comes from the change in education quality brought about by the SDA policy.

Another consideration is that the potential residential sorting between the treatment group and the control group might bias the estimation. A good method to tackle this problem is to control the population and income characteristics of the neighborhoods. But the income data at the community level is not available. Instead, we can view the housing price as a proxy of income level. A *t*-test shows that there is no significant price difference between the treatment group and the control group prior to SDA (t value is −0.5859 and *p* value is 0.5584). And it means there is no obvious income sorting between the treatment group and the control group. It should be admitted that this examination is a suboptimal alternative when there is no sufficient data.

Upon eliminating the influence of unobserved factors, the price premium of the treatment group caused by SDA can be obtained. This depends on the magnitude of change in the education quality brought about by the policy as calculated by the following equation:

$$\alpha_1 \triangle Edu_j = \triangle HP_{treat} - \triangle HP_{control} = \left(HP_{treat,t=2} - HP_{treat,t=1}\right) - \left(HP_{control,t=2} - HP_{control,t=1}\right) \tag{3}$$

According to Eq. (3), the regression model of this study is set as follows:

$$HP = \alpha_0 + \alpha_1 \triangle Edu_j \times PostSDA_i + \alpha_2 PostSDA_i + \beta S_i + \lambda_j + \mu_t + \varepsilon_i \tag{4}$$

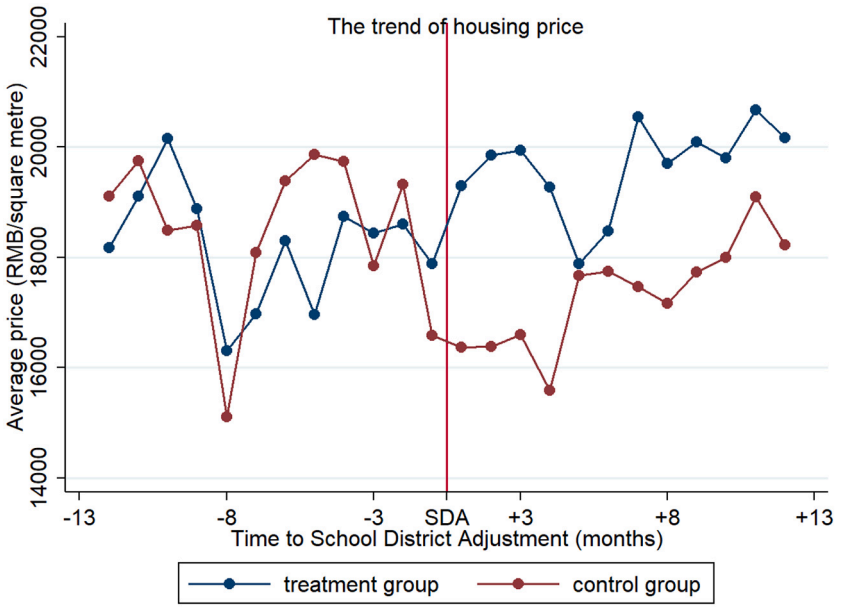

Fig. 2. The trend of price for treatment group and control group ($N_{Treat} = 754$, $N_{Control} = 553$).

Table 3
Examination of parallel paths.

	Housing price				
	(1)	(2)	(3)	(4)	(5)
Time of assumed treatment	April 2012 (1 month earlier)	March 2012 (2 months earlier)	February 2012 (3 months earlier)	February 2012 (4 months earlier)	February 2012 (5 months earlier)
*PostSDA * Treat*	1682.7	2491.0	2037.6	1425.0	947.0
	(1.28)	(1.88)	(1.47)	(1.22)	(0.74)
Treat	172.8	−166.1	−424.0	−337.8	−110.7
	(0.06)	(−0.06)	(−0.16)	(−0.14)	(−0.04)
PostSDA	−1933.2	−2532.0	−2279.4	**−1459.5***	−1255.0
	(−1.21)	(−1.48)	(−1.38)	**(−2.10)**	(−1.49)
N	276	276	276	276	276
R2	0.007	0.020	0.024	0.011	0.009

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We keep the observations before SDA and shift the time of treatment to an earlier date by 1–3 months. Then we apply the DID model to estimate the impact of assumed SDA. *PostSDA* indicates whether the transaction happens before the assumed adjustment or after. *Treat* indicates if the observation belongs to treatment group.

Table 4
Comparison of baseline features.

Variables	Control group	Treatment group	Difference	t value	p value
HP	17,965	18,306	−341	−0.5859	0.5584
Floor	8.2	11.3	−3.1	−2.9746	**0.0032*****
Age	7	5.4	1.6	3.3964	**0.0008*****
D_CBD	8.6	8.9	−0.3	−1.1752	0.2409
Q_transport	2.7	2.5	0.2	1.9982	**0.0467****
Q_nature	3.1	3.5	−0.4	−4.3808	**0.0000*****
Q_community	3.6	4	−0.4	−6.1940	**0.0000*****
Q_sports	3.8	3	0.5	2.8767	**0.0043*****

* p < 0.1, ** p < 0.05, *** p < 0.01.

where *PostSDA* is a dummy variable that indicates whether the transaction happens before the adjustment or after (experimental period); a time-constant dummy variable to indicate if the observation belongs to treatment group is omitted to avoid the collinearity with community fixed effects. $\triangle \boldsymbol{Edu}$ measures the change in neighborhood education quality after the adjustment and is time-constant. This change may be positive, negative, or zero (Table 5). It is not included in Eq. (4) because of the collinearity between

community fixed effects and $\triangle\boldsymbol{Edu}$. To avoid the estimation bias caused by small variance of some interaction term, education quality change is indicated by a continuous variable $\triangle\boldsymbol{Edu}$ rather than by separate dummy variables. For the housing belonging to the control group, the variable is automatically taken as 0. S_i, λ_j, μ_t and ε_i refer to architectural features, time-fixed effects, community fixed effects, and error items, respectively, which are similar to those described in Eq. (1).

In the DID model (4), $\triangle\boldsymbol{Edu}$ is collinear with the Treat variable so the interaction term is noted as $\triangle Edu \times PostSDA$. α_1 measures the capitalization effects of education quality but will only measure the average effect of the whole real estate market. If the capitalization effects are not symmetrically distributed in the market, although α_1 is unbiased, it cannot accurately describe the impact of educational facilities on housing prices under different circumstances. Therefore, we further used quantile regression (Chen, Kuan, & Lin, 2007; Jun, 2018a; Wen et al., 2019) to specify the variation of the capitalization effects. In contrast to dividing samples into several submarkets in accordance with a certain criterion (Jun, 2018; Ries & Somerville, 2010), a quantile regression model avoids bias in some submarkets caused by small samples. In other words, we can obtain an estimator in different quantiles to characterize the heterogeneity of capitalization effects α_1 under different situations. The quantile regression model was set as follows:

$$HP = \alpha_0(q) + \alpha_1(q)Edu + \alpha_2(q)Time + \alpha_3(q)Treat + \beta_i(q)S_i + \gamma_j(q)L_i + \delta_k(q)N_i + \lambda_j + \mu_t + \varepsilon_i \quad (5)$$

where q is the corresponding quantile of housing price; $\alpha_0(q)$, $\alpha_1(q)$, $\alpha_2(q)$, $\alpha_3(q)$, $\beta_i(q)$, $\gamma_j(q)$, and $\delta_k(q)$ are the q^{th} quantile coefficients to be estimated; and the remaining variables are similar to previous ones.

4. Empirical analysis

4.1. Baseline regression of the hedonic pricing model

First, we estimated Eq. (1) and Eq. (2) as the baseline model. The regression estimates the relative relationship between education quality and housing price through ordinary linear regression based on cross-sectional comparison strategies in previous studies. Table 6 shows the estimation.

This study focused on the capitalization effects of education quality, which is indicated by the regression coefficient α_1 of education quality (*Edu*) in Eq. (1). Table 6 shows a significant positive correlation exists between education quality and housing price. The results in column (1) show that the premium ranges 1663 yuan/m^2 after considering the influence of other control variables. However, the results in column (3) in Table 6 show that the estimation of the coefficient decreases after controlling for community fixed effects, thereby illustrating the presence of unobserved factors at the community levels affecting housing prices. This estimate is also more accurate than that in column (4) without controlling structural features: a one-level increase in education quality will increase the housing price by 693 yuan/m^2. This price premium is significant at the confidence level of 5%.

4.2. Regression of DID

However, apart from the unobservable factors on community and time level, unobserved individual features and macroeconomic characteristics continue to affect housing prices. Unawareness of these factors will also lead to estimation bias. Therefore, we needed to further use the DID model of Eq. (4) to estimate the capitalization effects brought about by the promoted quality of educational facilities. Table 7 shows the regression results.

The results of column (2) in Table 7 show that the change in education quality brought about by the SDA has resulted in a significant housing premium, which can reach 817 yuan/m^2, considering the time and community fixed effects. In comparison with the results of the baseline regression, the premium has increased by approximately 120 yuan/m^2. This difference is mainly due to the influence of unobserved factors, including improved macroeconomic characteristics and high value of houses near high-quality schools. Previous studies have neglected these omitted factors, causing downward estimation bias. In addition, the change in estimation when control variables and fixed effects are considered is similar to the baseline regression.

4.3. Robust test

Because this research cares more about the price effects brought by education quality change in SDA, a robust test is carries out in this part to investigate the mechanism of the capitalization effects.

Table 5
Education quality change.

Obs.	School districts	Communities	Houses	Houses before SDA	Houses after SDA
Control group	7	30	553	113	440
Treatment group	7	17	754	163	591
$\triangle Edu = -1$	1	1	1	0	1
$\triangle Edu = 0$	2	4	234	60	174
$\triangle Edu = 1$	3	8	499	101	398
$\triangle Edu = 2$	1	1	8	1	7
$\triangle Edu = 3$	1	2	12	1	11

Table 6
Baseline regression of hedonic price model based on cross-sectional comparison.

	Housing price			
	(1)	(2)	(3)	(4)
	Eq. 1	Eq. 1 with time FE	Eq. 2	Eq. 2 without control variables
Education quality (Edu)	**1663.1*****	**1663.1*****	**693.0****	**971.1****
	(5.45)	**(5.41)**	**(3.01)**	**(2.97)**
Age	**−302.6*****	**−315.3*****	**319.9***	
	(−4.16)	**(−4.38)**	**(2.24)**	
Floor	**31.10***	29.00	17.26	
	(1.95)	(1.83)	(1.39)	
D_CBD	**−2176.1*****	**−2179.5*****		
	(−12.52)	**(−13.02)**		
Q_transport	−558.3	−546.9		
	(−1.00)	(−1.03)		
Q_nature	943.2	**946.8***		
	(1.80)	**(1.84)**		
Q_community	**1263.5*****	**1237.5*****		
	(5.36)	**(5.51)**		
Q_sports	**29,437.8*****	0.586		
	(10.68)	(0.00)		
Time FE	×	√	√	√
Community FE	×	×	√	√
N	1307	1307	1307	1307
R2	0.607	0.613	0.767	0.766

* p < 0.1, ** p < 0.05, *** p < 0.01; t in parenthesis.

Table 7
Regression of Difference-in-differences.

	Housing price	
	(1)	(2)
	Eq. 4 without control variables	Eq. 4
△*Edu* * *PostSDA*	**801.0****	**817.8****
	(3.12)	**(3.18)**
PostSDA	188.2	**−730.1***
	(1.67)	**(−1.99)**
Age		**931.5****
		(2.29)
Floor		18.05
		(1.43)
Time FE	√	√
community FE	√	√
N	1307	1307
R^2	0.766	0.767

* p < 0.1, ** p < 0.05, *** p < 0.01; t in parenthesis.

First, in column (2), housing in the community that has undergone SDA but has unchanged neighborhood education quality is removed. The coefficient of interaction term (△*Edu* * *PostSDA*) captures the price premium when the neighborhood education quality is enhanced by one level. The result in column (2) demonstrates that when neighborhood education quality is enhanced by one level, the housing price will increase by 693 yuan/square metre. The price effects could be much larger when the education quality is enhanced by two level.

Second, in column (3), housing in the community that has undergone SDA but has unchanged neighborhood education quality is kept as the treatment group. Housing with changed education quality is removed. The result can be viewed as a placebo test, which suggests that although some housing has undergone SDA, there is no obvious price effect if the education quality is not promoted. The education uncertainty might cause a decrease of housing value (Cheshire & Sheppard, 2004), though this depreciation effect is not significant in this paper. This placebo test also demonstrates the importance of facility quality change when probing the price effects of educational policies. The educational policies will not bring about housing price change directly. The housing prices change significantly, only if the policy affects public service quality which people obtain.

Third, in column (4), only housing whose education quality increases by one level is kept as treatment group. A simple DID model is constructed here as a reflection to previous studies. The estimation can be viewed as housing price effects of one policy without considering the facility quality change. As pervious research finds (Bogart & Cromwell, 2000), the result in column (4) shows that SDA policy contributes in a price premium at around 900 yuan/square metre. Combined with estimation in other regressions, this paper supplemented mechanism of the price effects, which is one of the main contribution.

4.4. Heterogeneity regression

The literature review shows that a premium of 817 yuan/m^2 only describes the average reaction of the price to the education quality, which is not enough to describe the impact of public goods upon different types of second-hand houses. Therefore, in the following part, we detail our analysis of the variation of capitalization effects by combining the quantile regression and DID models. We also compare the capitalization effects by dividing the sample into different groups according to housing areas.

Quantile regression specifies the varying price effects on houses with different value. Table 9 shows the results of Eq. (5) and demonstrates that education quality has a significant positive impact on houses that have a lower price than the 50th quantile. In other words, educational facilities have no obvious impact on high-priced housing but only on low-priced housing. With the price decreases to the 20th quantile, the capitalization effects are becoming increasingly significant and larger. For instance, low-priced housing can obtain a premium much higher than the average. This premium is significant at the confidence level of 0.01. By contrast, medium-priced housing can only obtain a premium lower than the average.

We can also intuitively express the heterogeneity across the contribution when quantiles change. The horizontal dash line represents the coefficients and corresponding confident intervals of ordinary linear regression, and the green solid line represents the quantile regression coefficients and corresponding confidence intervals. The Fig. 3 shows that capitalization effects are not symmetrically distributed in the real estate market but rise with the decrease in housing prices. This premium begins to become significant at 40%. This result reinforces the conclusion that the value of housing is universally affected by educational public goods, whereas the value of high-priced housing is not, or even not affected by educational quality change. Fig. 4 is other relevant coefficients estimated by combination of quantile regression and DID.

Further, we divided the sample into two according to whether housing area is larger than 100 square metre. Table 10 shows the results of Eq. (4) and illustrates that education quality affects small houses much more than large houses. The price premium for small houses can touch 1000 while large houses remain statistically unaffected. This phenomenon might come from facts that people do not buy houses with better nearby school for long-time residence. Instead, they only value the education quality and resell it after their children finish primary education. Given the financial burden of high payment and parents' overlook of living space, small houses are more ideal to keep. Therefore, the demand for small houses is much higher and their price are more affected by SDA.

5. Discussion

In China, housing is the major mediator for residents to access public primary education and the quality of neighborhood school is an important determinant when citizens buy houses. Local governments always propose educational policy to balance the supply and the demand, as well as to provide children with equal opportunity to develop. But how the quality capitalization effects change during a policy is not clear in previous studies. Therefore, based on the Hangzhou's school district adjustment in 2012, this paper investigated housing price effects of policies and education quality changes, rather than a static educational facility. Then we used transaction data of each second-hand house to directly reflect the discussion of Oates (1969) that the improvement of local public goods supply has a positive impact on housing prices and purchasing costs of residents.

By utilizing DID, this study also calculated a more accurate capitalization effects at 817 yuan/m^2 for every level of increase in education quality during SDA. Compared with previous studies on educational capitalization effects, this estimation makes two differences. First, previous studies show that houses with a first-level nearby school have a price premium of 1.5% than houses with a second-level school (Wen et al., 2017). It does not mean that the housing price will increase by 1.5% if the neighborhood education quality is promoted by one level under public policies. In fact, our models show that the price effects of education quality with a policy context are much higher (4.4%) than previous static estimation. It also illustrates that the capitalization effects of governmental

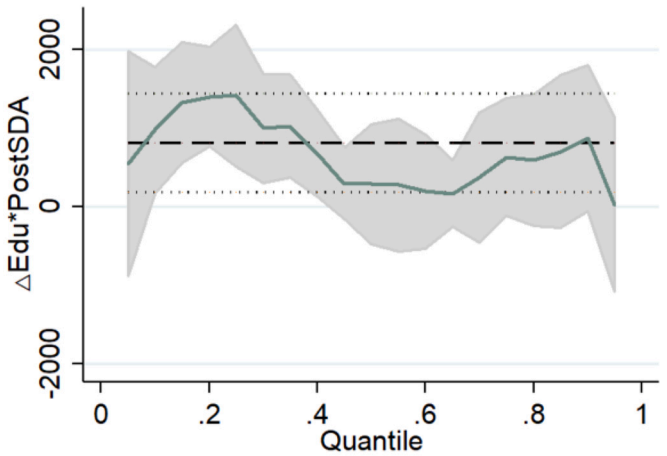

Fig. 3. price premium brought by a promotion in education quality changes when the price changes.

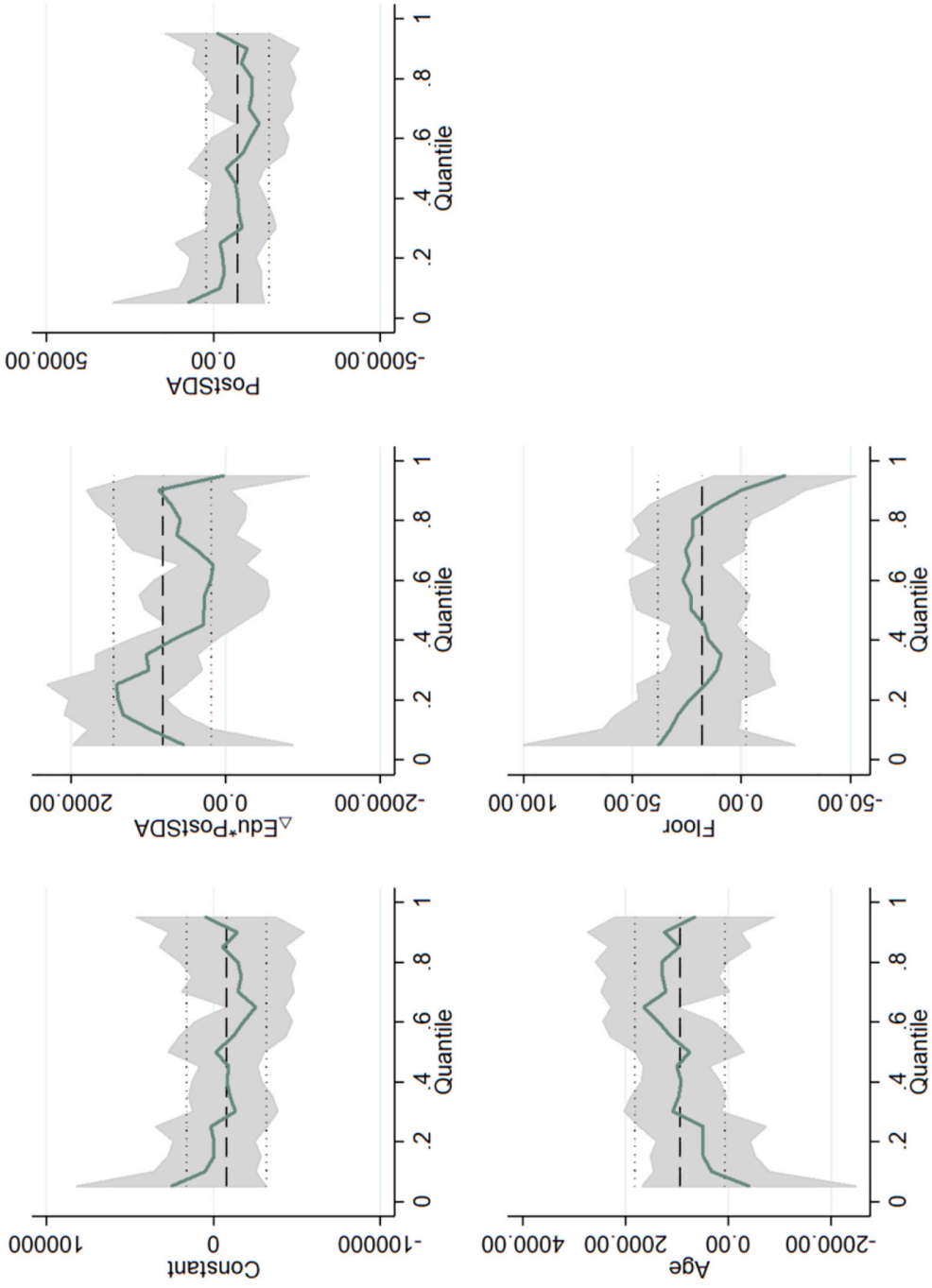

Fig. 4. coefficients estimated by combination of quantile regression and DID.

intervention are higher than that caused by market mechanism. Ignorance of this distinctive difference might lead to a downward evaluation of educational policy. More importantly, what is underestimated is the dramatically increased housing prices affected by the policy implementation. Previous studies verified price effects of educational policies (Feng & Lu, 2013), but their overlook of education quality change results in an ignorance of an importance fact. The fact is that local governments promote some houses' education quality, to balance the supply and demand, as well as relieve parents' burden and realize the educational equity. However, those policies fail to achieve their goals. Instead, they make existing education resources more expensive for low-income people than before. Additionally, the educational policy would enlarge the wealth gap between people in different groups. And this is the reason why we put emphasis upon the quality change during SDA rather than SDA itself and contributed to the previous studies.

While using the DID, we adopted measures to enhance the robustness of the analysis. One is the explanation about the SDA as a perfect background and the parallel paths of housing prices between the control and treatment groups, which has been neglected by related DID studies. Although this added explanation on this point cannot help improve the accuracy of the analysis, it helps to avoid selection bias (Heckman & Jr, 1985), improve the methodological deficiencies of the relevant research, and enhance the reliability of the analysis. The other contribution of our study is that we did several robust tests and revealed how educational policy affects people's behaviors. Previous studies have shown educational policy has significant price effects (Feng & Lu, 2013) and we found that an important premise of policy impact is the promotion of education quality. Placebo test in Table 8 demonstrates that housing prices do increase significantly only if nearby school becomes better. Even some housing has undergone SDA, there is no obvious price effect if their education quality is not promoted.

Finally, we combined the DID model with quantile regression and divided regression to find the heterogeneous effects of educational polices. If governments propose policies without considering the heterogeneous effects, policies with a good faith might benefit the minority, hurt the majority and aggravate the education inequity. This heterogeneous estimation helps to uncover educational pressure under changed policies and provide policy implication more precisely. We found that low-priced housing tends to have a high price premium of up to 1401 yuan/m2. Fig. 3 also shows that the significant capitalization effects will increase dramatically when the housing price decrease. This heterogeneity is contrary to Ries and Somerville (2010), probably because the conflict between the demand for high quality education resources and urban planning strategies is more intense in China. Specifically, houses that have a low price around the 20th quantile will obtain a largest price premium. Small houses are affected more by education quality promotion during SDA. It can be consequence of facts that people only view those houses as a stepping stone to better educational facilities rather than a residence.

The quantile estimation provides a deep understanding of education-induced competition in the housing market when local bureau proposes public policies. The variation of the capitalization effects means that the promotion of education quality results in price premiums to different degrees. It also reflects that the demand for housing increases to a different extent. The results in Table 9 and Fig. 3 can be further interpreted as follows: when SDA happens, number of potential purchasers for low-priced housing goes up dramatically, whereas there is no significant change upon buyers of high-priced housing. This difference may be caused by the phenomenon called education-led gentrification (Wu, Zhang, & Waley, 2016). Although buyers of high-priced housing are not necessarily from a high-income group, they have stronger consumption capability to improve their expenditure structure (Wen et al., 2019). They are moving in the indigenous housing to be a registered resident in the catchment area of a top primary school. Potential buyers of low-priced houses are likely to be low-income groups, and for them, transportation accessibility may be most important (Wu et al., 2013; Yang, Chau, & Wang, 2019). Therefore, they may prefer to choose housing with convenient public transportation and easy commuting. Accordingly, they reduce their educational demand to coordinate their insufficient affordability. When educational policy promotes school quality of low-priced housing, if no policy regulation exists, the improved education resources will attract both low-income and high-income people and eventually be sold to the groups with more economic capital. This circumstance results in the gradual displacement of low-income people in low-priced housing (Guerrieri, Hartley, & Hurst, 2013), which ultimately makes it impossible to secure high-quality education or a place to live for those in low-income group. The quantile regression shows that the above educational expel involves a wide range of houses and population (more than 40%).

The higher price premium of small houses in SDA reveals citizens' compromise for better education. Parents regard the houses with better school as a qualification for their children to have education, rather than a house to live in. Therefore, small houses are more welcome when public policy promotes the facility quality. The buyers either quarter in the small house and resell the house after their kids finish primary education, or live in a larger house far away and commute a long distance for school. The former situation leads to a decrease in life condition and the latter situation results in an increase in students' burden and urban transport. Both situation would stimulate the housing market and related speculation, causing housing price more and more unaffordable. More importantly, it is citizens with limited income who trade living condition for better educational resource. It is more and more difficult to realize educational equity in society with a booming housing price.

6. Conclusions and suggestions

Investigating the capitalization effects of education quality change is one of the important ways to research local public goods allocation and analyze the causes of housing price fluctuations. However, previous discussions on this problem neglect potential endogeneity issues, which lead to estimation bias. Extant studies often overlook the heterogeneity in the market, thereby resulting in one-sided conclusions. To address such problems, this study took the public primary SDA in Hangzhou in 2012 as an example. Our analysis extended a DID model with quantile regression and divided regression, and our results show that the transaction price of second-hand houses increases by 817 yuan/m^2 on average for a one-level increase in the quality of educational facilities. The value-added effects are more obvious for low-priced houses and small houses, with a premium of more than 1000 yuan/m^2, than for high-

Table 8
Robust test of Difference-in-differences.

	Housing price			
	(1)	(2)	(3)	(4)
	Baseline DID	△Edu = 0 deleted	Placebo test	△Edu ≠ 1 deleted
△*Edu* * *PostSDA*	**817.8****	**693.1***	−337.4	**923.6*****
	(3.18)	**(1.96)**	(−1.75)	**(3.76)**
PostSDA	−730.1*	−878.7**	−340.3	−1084.6***
	(−1.99)	(−3.03)	(−0.79)	(−4.41)
Age	**931.5****	**1243.7*****	**585.0**	**1384.3*****
	(2.29)	**(5.46)**	**(1.35)**	**(6.74)**
Floor	18.05	15.45	22.86	15.81
	(1.43)	(1.11)	(1.15)	(1.13)
Time FE	√	√	√	√
Community FE	√	√	√	√
N	1307	1073	787	1052
R2	0.767	0.591	0.807	0.723

* p < 0.1, ** p < 0.05, *** p < 0.01; t in parenthesis.

Table 9
Heterogeneity revealed by combination of Difference-in-differences and quantile regression.

	Housing price									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantile	Baseline	10th	20th	30th	40th	50th	60th	70th	80th	90th
△*Edu* * *PostSDA*	**817.8****	**974.5****	**1401.3*****	**996.9****	**682.6***	288.4	195.7	373.2	595.1	870.3
	(3.18)	**(2.00)**	**(3.49)**	**(2.54)**	**(1.96)**	(0.75)	(0.47)	(1.00)	(1.29)	(1.53)
PostSDA	−730.1*	−189.1	−274.9	−841.5	−723.7	−378.0	**−1109.0***	**−1065.2***	**−1148.0***	−1014.7
	(−1.99)	(−0.26)	(−0.46)	(−1.44)	(−1.39)	(−0.66)	**(−1.78)**	**(−1.91)**	**(−1.67)**	(−1.20)
Age	**931.5****	323.2	492.9	**1085.9****	**923.7***	760.6	**1374.5****	**1226.7****	**1304.9****	1255.3
	(2.29)	(0.48)	(0.88)	**(1.99)**	**(1.91)**	(1.42)	**(2.37)**	**(2.36)**	(2.04)	(1.59)
Floor	18.05	**32.84****	**23.94***	11.50	15.40	23.26*	**27.01****	**26.07****	22.89	0.00
	(1.43)	**(2.10)**	**(1.86)**	(0.91)	(1.37)	(1.88)	**(2.01)**	**(2.17)**	(1.55)	(0.00)
Time FE	√	√	√	√	√	√	√	√	√	√
Community FE	√	√	√	√	√	√	√	√	√	√
N	1307	1307	1307	1307	1307	1307	1307	1307	1307	1307

* p < 0.1, ** p < 0.05, *** p < 0.01; t in parenthesis.

Table 10
DID heterogeneity revealed by dividing the sample.

	Housing price		
	(1)	(2)	(3)
	All houses	Small houses	Large houses
△*Edu* * *PostSDA*	**817.8****	**1061.3*****	199.7
	(3.18)	**(3.65)**	(0.83)
PostSDA	**−730.1***	−847.0	−414.8*
	(−1.99)	(−1.29)	(−2.36)
Age	**931.5****	1467.9	349.1
	(2.29)	(1.69)	(1.72)
Floor	18.05	**29.28*****	14.80
	(1.43)	**(14.02)**	(0.59)
	(3.40)	**(2.91)**	(0.07)
Time FE	√	√	√
community FE	√	√	√
N	1307	644	663
R2	0.767	0.782	0.765

* p < 0.1, ** p < 0.05, *** p < 0.01; t in parenthesis.

priced houses. However, the effects are not significant for houses that have a price above the 40th quantile.

This work makes three main improvements. First, this study took each set of second-hand housing as the object and utilized microeconomic transaction data, which can capture detailed factors. Second, with the help of the quasi-experimental background of SDA in Hangzhou, this work applied DID and achieved an accurate estimation of the capitalization effects. This study emphasized the

randomness of grouping and the premise of parallel paths of the quasi-experiments. Third, this paper depicted submarket heterogeneity via quantile regression and divided regression to uncover mechanism of the capitalization effects.

In addition to theoretical improvements, this research is significant to policymaking. First, education quality change after the policy implementation is the source of price effects, increasing educational burden and worsening educational equity. Balancing the school quality in urban area and dispelling parents' stereotyping toward different school quality is the permanent cure to these social dilemmas. Second, low-income groups are disadvantaged in the competition for better education. Education bureau should effectively protect the rights of low-income groups and ensure that they can have equal opportunities for education. Otherwise, the allocation of educational resources will be extremely stratified by two distinct preferences, which eventually leads to the immobility of social strata. Finally, clearly-targeted policies are needed. The speculation of small houses should be strictly controlled. The added value of high-priced houses should be captured through taxation and the appropriate tax rate is higher than that in previous estimation (Wen et al., 2019).

Future research can be improved from several perspectives. First, the housing price gap between the treatment group and the control group is not significant, which can demonstrate that there is no obvious income sorting. But the population and income characteristics could be controlled with available data to tackle the problem of residential sorting more precisely. Second, this work regarded the quality of education as a continuous variable, which implies that the differences between different levels of education quality are equal and comparable. However, the capitalization effects of education quality are neither necessarily equidistant nor linear. Third, the distribution of housing prices is spatially autocorrelated. Combining a spatial econometric model can further enhance the predictive power of the model and depict spatial variation.

Funding

This study was funded by the National Social Science Foundation of China(No: 17BJY224), the National Natural Science Foundation of China (No:71974169), the Fundamental Research Funds for the Central Universities, the Strategic Development Research Platform of Hangzhou City-Zhejiang University, and the Peking University-Lincoln Institute Center for Urban Development and Land Policy. All errors remain are our own.

References

Alonso, W. (1964). Location and land use. Toward a general theory of land rent. *Economic Geography, 42*(3), 11–26.
Ashenfelter, O., & Card, D. (1984). *Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs* (pp. 648–660). Elsevier Science Publishers B.V. (North-Holland).
Bae, H., & Chung, I. H. (2013). Impact of school quality on house prices and estimation of parental demand for good schools in Korea. *Kedi Journal of Educational Policy, 10*(1), 43–61.
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.
Bayer, P., Mcmillan, R., & Rueben, K. S. (2004). What drives racial segregation? New evidence using census microdata. *Journal of Urban Economics, 56*(3), 514–535.
Beracha, E., & Hardin, W. G. (2018). The capitalization of school quality into renter and owner housing. *Real Estate Economics, 46*.
Besley, T., & Case, A. (2000). Unnatural experiments? Estimating the incidence of endogenous policies. *Economic Journal, 110*.
Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *Research Paper, 114*(2), 577–599.
Bogart, W. T., & Cromwell, B. A. (2000). How much is a neighborhood school worth? *Journal of Urban Economics, 47*(2), 280–305.
Callaway, B., Li, T., & Oka, T. (2018). Quantile treatment effects in difference in differences models under dependence restrictions and with only two time periods. *Journal of Econometrics, 206*.
Chan, K. W. (2009). The Chinese Hukou system at 50. *Eurasian Geography and Economics, 50*(2), 197–221.
Chan, K. W., Liu, T., & Yang, Y. (1999). Hukou and non-hukou migrations in China: Comparisons and contrasts. *International Journal of Population Geography, 5*(6), 425–448.
Chen, C. L., Kuan, C. M., & Lin, C. C. (2007). Saving and housing of Taiwanese households: New evidence from quantile regression analyses. *Journal of Housing Economics, 16*(2), 0–126.
Cheshire, P., & Sheppard, S. (2004). Capitalizing the value of free schools: The impact of supply constraints and uncertainty. *The Economic Journal, 114*, 397–424.
Christopher, D. (2019). Higgins. A 4D spatio-temporal approach to modelling land value uplift from rapid transit in high density and topographically-rich cities. *Landscape and Urban Planning, 185*, 68–82.
Colin Cameron, A., & Miller, D. L. (2015). A practitioner's guide to cluster- robust inference. *The Journal of Human Resources, 50*, 317–372.
Collins, C. A., & Kaplan, E. K. (2017). Capitalization of school quality in housing prices: Evidence from boundary changes in Shelby County. *Tennessee. American Economic Review, 107*(5), 628–632.
David, S. (2011). Capitalisation of fiscal variables and land scarcity. *Crema Working Paper, 49*(2010−03), 1571–1594.
Dhar, P., & Ross, S. L. (2012). School district quality and property values: Examining differences along school district boundaries. *Journal of Urban Economics, 71*(1), 18–25.
Emran, M. S., Robano, V., & Smith, S. C. (2009). *Assessing the Frontiers of ultra-poverty reduction: Evidence from CFPR/TUP*. SSRN Electronic Journal: An Innovative Program in Bangladesh.
Feng, H., & Lu, M. (2013). School quality and housing prices: Empirical evidence from a natural experiment in Shanghai. *China. Journal of Housing Economics, 22*(4), 291–307.
Gibbons, S., Machin, S., & Silva, O. (2013). Valuing school quality using boundary discontinuities. *Journal of Urban Economics, 75*(1), 15–28.
Goodman, A. C., & Thibodeau, T. G. (2010). The Spatial Proximity of Metropolitan Area Housing Submarkets. *Real Estate Economics, 35*(2), 209–232.
Guerrieri, V., Hartley, D., & Hurst, E. (2013). Endogenous gentrification and housing price dynamics. *Journal of Public Economics, 100*(16237), 45–60.
Heckman, J. J., & Jr, R. R. (1985). Alternative methods for evaluating the impact of interventions : An overview. *Journal of Econometrics, 30*(1), 239–267.
Huang, P., & Hess, T. (2018). Impact of Distance to School on Housing Price: Evidence from a Quantile Regression. *Empirical Economics Letters*, 17(2).
Jun, M. J. (2018). Quantifying Welfare Impacts of Air Pollution in Seoul: A Two-Stage Hedonic Price Approach. *Journal of Environmental Assessment Policy and Management*, 20(02).
Kahn-Lang, A., & Lang, K. (2020). The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications. *Journal of Business & Economic Statistics, 38*, 613–620.
Kirstine, H. (2014). Moving house for education in the pre-school years. *British Educational Research Journal, 40*(3), 483–500.
Lancaster, K. (1966). J. a new approach to consumer theory. *Journal of Political Economy, 74*(2), 132–157.

Livy Mitchell, R. (2017). The effect of local amenities on house price appreciation amid market shocks: The case of school quality. *Journal of Housing Economics, 36*, 62–72.
Mao, F., Luo, G., & Pan, J. (2014). Study on the impact of high-quality educational resources on housing prices in Hangzhou School District. *Urban and Environmental Studies, 2*, 53–64 [In Chinese].
Meyer, & Breed, D. (1995). Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics, 13*(2), 151–161.
Mora, R., & Reggio, I. (2015). Didq: A command for treatment-effect estimation under alternative assumptions. *The Stata Journal, 15*(3), 796–808.
Mulligan, G. F., Franklin, R., & Esparza, A. X. (2002). Housing prices in Tucson. *Arizona. Urban Geography, 23*(5), 446–470.
Newsome, B. A., & Zietz, J. (1992). Adjusting comparable sales using multiple regression analysis — The need for segmentation. *The Appraisal Journal*, 129–135.
Nguyen-Hoang, P., & Yinger, J. (2011). The capitalization of school quality into house values: A review. *Journal of Housing Economics, 20*(1), 0–48.
Oates, W. E. (1969). The effects of property taxes and local public spending on property values: An empirical study of tax capitalization and the Tiebout hypothesis. *Journal of Political Economy, 77*(6), 957–971.
Pilgram, C. A., & West, S. E. (2018). Fading premiums: The effect of light rail on residential property values in Minneapolis. *Minnesota. Regional Science & Urban Economics, 69*.
Ries, J., & Somerville, T. (2010). School quality and residential property values: Evidence from Vancouver rezoning. *Review of Economics & Statistics, 92*(4), 928–944.
Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.
Rosenthal, L. (2003). The value of secondary school quality. *Oxford Bulletin of Economics and Statistics, 65*(3), 329–355.
Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy, 64*(5), 416–424.
Turnbull, G. K., Zahirovic-Herbert, V., & Zheng, M. (2018). Uncertain school quality and house prices: Theory and empirical evidence. *The Journal of Real Estate Finance and Economics, 57*(2), 167–191.
Wen, H., Gui, Z., Tian, C., Xiao, Y., & Fang, L. (2018). Subway Opening, Traffic Accessibility, and Housing Prices: A Quantile Hedonic Analysis in Hangzhou, China. *Sustainability*, 10(7).
Wen, H., Lu, J., & Fu, Y. (2005). *Product differentiation and hedonic prices: An empirical analysis// International Conference on Services Systems & Services Management*. IEEE.
Wen, H., Xiao, Y., & Hui, E. C. M. (2019). Quantile effect of educational facilities on housing price: Do home buyers of higher-priced housing pay more for educational resources? *Cities, 90*, 100–112.
Wen, H., Xiao, Y., Hui, E. C. M., & Zhang, L. (2018). Education quality, accessibility, and housing price: Does spatial heterogeneity exist in education capitalization? *Habitat International, 78*, 68–82.
Wen, H., Xiao, Y., & Zhang, L. (2017). School district, education quality, and housing price: Evidence from a natural experiment in Hangzhou. *China. Cities, 66*, 72–80.
Wen, H., Zhang, Y., & Zhang, L. (2014). Do educational facilities affect housing price? An empirical study in?Hangzhou. *China. Habitat International, 42*, 155–163.
Wu, Q., Zhang, X., & Waley, P. (2016). Jiaoyufication: When gentrification goes to school in the Chinese inner city. *Urban Studies, 201653*, 3510–3526.
Wu, W., Zhang, W., & Dong, G. (2013). Determinant of residential location choice in a transitional housing market: Evidence based on micro survey from Beijing. *Habitat International, 39*, 16–24.
Yang, J., Chen, J., & Le, X. (2016). Density-oriented versus development-oriented transit investment: Decoding metro station location selection in Shenzhen. *Transport Policy, 51*, 93–102.
Yang, L., Chau, K. W., & Wang, X. (2019). Are low-end housing purchasers more willing to pay for access to basic public services? *Evidence from China. Research in Transportation Economics, 76*, 100734.
Zahirovic-Herbert, V., & Turnbull, G. K. (2008). School quality, house prices and liquidity. *Journal of Real Estate Finance and Economics, 37*(2), 113–130.
Zhang, Y., & Dong, R. (2018). Impacts of street-visible greenery on housing prices: evidence from a hedonic price model and a massive street view image dataset in Beijing. *International Journal of Geo-Information*, 7(3).
Zheng, S., Hu, W., & Wang, R. (2015). How much is a good school worth in Beijing? Identifying Price premium with paired resale and rental data. *The Journal of Real Estate Finance and Economics, 53*(2), 1–16.